Emily Dovydaitis[1], Thomas Kunze[2], Fabian Born[3], Frank Ewert[1], Silke Dachbrodt-Saaydeh[2], Kathrin Grahmann[1]

Assessing pollen beetle dynamics in diversified agricultural landscapes with reduced pesticide management strategies

Exploring the potential of digital yellow water traps for continuous, high-resolution monitoring in oilseed rape

Affiliations

[1] Leibniz Centre for Agricultural Landscape Research (ZALF), Müncheberg, Germany.

[2] Julius Kühn Institute (JKI) – Federal Research Centre for Cultivated Plants, Institute for Strategies and Technology Assessment, Kleinmachnow, Germany.

[3] Bayer AG – Laacher Hof, Monheim am Rhein, Germany.

Correspondence

Kathrin Grahmann, Dr. agr., Leibniz Centre for Agricultural Landscape Research (ZALF), Eberswalder Straße 84, 15374 Müncheberg, Germany, email: kathrin.grahmann@zalf.de

Summary

The European Farm to Fork strategy strives to reduce pesticide use and risk by 50% by 2030, preserving agricultural productivity, biodiversity, and human health. Novel research on crop diversification and new field arrangements, supported by digital technologies, offers sustainable innovations for pest control. This study evaluates digital yellow water traps, equipped with a camera and associated artificial intelligence model for continuous pollen beetle monitoring in diversified agricultural landscapes. Data were collected in oilseed rape from three harvest years (2021–2023) at the experimental site patchCROP, a landscape experiment established to study the effects of spatial and temporal crop diversification measures on yield, ecosystem services, and biodiversity. In patchCROP, crops were planted in smaller, 0.5 ha (72 × 72 m) squares called “patches" with different pesticide management strategies and were compared to surrounding commercial fields. The digital yellow water traps and AI were evaluated and found to be useful for gauging pollen beetle immigration into the crop. Across all years, higher insect pest pressure was recorded in the patches compared to commercial fields but did not necessarily compromise yields. Implementation of pesticide management strategies, including targeted insecticide applications at specific insect pest thresholds, were not associated with reduced yields in patches with flower strips. Future studies should consider examining the role of field size and alternative diversification approaches to fine-tune insecticide reduction strategies at the landscape scale.

Keywords

rapeseed, *Brassica napus*, digital technologies, camera, artificial intelligence, diversification, flower strips

1. Introduction

Global trends indicate a decrease in biodiversity associated with agriculturally managed lands (Landis, 2017). In addition to agricultural intensification, characterized by habitat loss, intense land-use, and fertilizer application, and other global challenges, including climate change, urbanization, and pollution, plant protection products (hereafter pesticides) play a major role in the decline of insect species diversity in Europe (Habel et al., 2019). Agricultural diversification, and in particular crop heterogeneity, was found to effectively increase biodiversity (Sirami et al., 2019). Diversified cropping systems with new spatial field arrangements, wider crop rotations, and site-specific crop selection require innovative technologies to support the decision-making regarding crop protection measures. These new technologies can serve as monitoring tools and are ideally tested in the agricultural landscape context in collaboration with farmers (Busse et al., 2021).

The demand for rapeseed oil, the product of *Brassica napus* L., commonly called oilseed rape (OSR), is increasing in Europe (Vinnichek et al., 2019); however, producers face several challenges. Farmers often face competition from global OSR markets (Busse et al., 2021). Under conventional management, OSR requires high levels of nutrient inputs, intensive pest monitoring, and pesticide applications. Compared to OSR disease management, insect pest control presents a greater challenge due to the limited range of available management options; as a result, insect pest control heavily relies on insecticides (Zheng et al., 2020). When applied prophylactically and routinely, insecticides can decrease economic competitiveness of OSR, encourage resistance in insect pest species, and reduce parasitoid populations which act as biological control (Williams, 2010).

Some of the major OSR insect pests in Germany include pollen beetles (*Brassicogethes aeneus*), cabbage stem flea bee-

Submitted/accepted for publication: 25 August 2023/18 December 2023

tles (*Psylliodes chrysocephala*), various weevil species (*Ceutorhynchus picitarsis*, *C. pallidactylus*, *C. obstrictus*), and the brassica pod midge (*Dasineura brassicae*) (Williams, 2010). In some hotspots like Germany, Poland, and the UK, OSR producers are coping with an increased insect pest burden (Arthey, 2020), including the increasing trend of pollen beetles (Shortall et al., 2023) and cabbage stem flea beetle larvae in the UK (Ortega-Ramos et al., 2023). Insect pest management is further complicated by legal insecticide regulations and prohibitions of certain active ingredients, including the EU ban on neonicotinoid seed treatments (Lundin, 2021). High levels of pyrethroid resistance in OSR insect pests (Zheng et al., 2020), particularly in the pollen beetle (Heimbach & Müller, 2012), and increasingly in seed weevil species (Daum et al., 2023), underscore the risks of relying on one mode of action for pest management. New control strategies are needed (Daum et al., 2023), particularly non-chemical ones (Heimbach & Müller, 2012), to manage insect pests in OSR. Biocontrol agents, including parasitoids and natural predators, (Williams, 2010), could help alleviate some of these challenges.

In addition to increased research on and use of biocontrol agents, adjustment of insect pest management strategies is crucial. In the literature, various agricultural diversification strategies were identified to increase biodiversity and reduce the demand for external inputs like pesticides without compromising crop yield (Tamburini et al., 2020). Changing landscape configuration, such as using smaller fields, has been shown to support the complementary goals of arthropod pest suppression and enhanced cropland biodiversity (Haan et al., 2020). Using alternative or integrated pest management (IPM) strategies can curb pest populations without the excessive application of pesticides. Improved and reliable insect pest monitoring can lead to earlier detection of pests (Bick et al., 2023), allow for precise pesticide application (Döring et al., 2012), and help OSR producers adjust their management strategies (Ortega-Ramos et al., 2023). Precise monitoring could also be used to forecast pollen beetle abundance (Shortall et al., 2023), detect their immigration into OSR (Bick et al., 2023), and provide early warnings to farmers.

The potential of OSR insect pests to damage and reduce yield depends on the crop's growth stage. Insect pest species immigrate into the rapeseed crop at different times (supplementary Fig. S1), further complicating their management. For example, pollen beetles are monitored using yellow water traps and visual inspections of OSR plants (Bartels et al., 2023). From stem elongation until the beginning of flowering (BBCH 30–60), yellow water traps help detect and estimate pollen beetle immigration. During inflorescence emergence (BBCH 50–60), an insect pest monitoring method known as plant scouting or plant beating is performed (Metspalu et al., 2015). To carry out plant beating, a tray is held under the main shoot and the main shoot is hit multiple times. The pollen beetles which fall off are counted and used to estimate adult pollen beetle abundance. If the pollen beetle threshold per main inflorescence is exceeded, insecticides are applied to conventionally managed crops. Throughout the relevant BBCH stages, yellow water traps are monitored, and plant beating is performed every three to four days.

Compared to cereals like winter wheat and winter barley, farmers in Germany spend more than double the amount of time monitoring insect pests in OSR (Thiel et al., 2023). Although the potential to reduce insecticide usage via pest thresholds without reducing yield is also higher in OSR, the time spent monitoring pests presents a significant economic burden when labour costs are high and insecticide costs are low (Thiel et al., 2023). Current precise pest monitoring methods are often time-consuming, labour-intensive, and require specific taxonomic knowledge, as such it is especially important to implement innovative, affordable, human-centred design; one such solution is artificial intelligence (AI)-powered pest monitoring (Montgomery et al., 2021; Rosado et al., 2022). Digitalization, characterized by the use of digital tools, technologies, sensors, and robots to assist with or perform tasks in an agricultural setting, also has great potential in transforming pest monitoring and management (Cardim Ferreira Lima et al., 2020; Preti et al., 2021). One such digital technology is optical sensors, which allow for earlier detection of pollen beetle immigration into OSR (Bick et al., 2023). Comprehensive, digitalized monitoring of pest dynamics would allow for more precise and situation-specific application of pesticides.

In this study, the new technology of digital yellow water traps (DYWTs) was compared to yellow water traps (YWTs), also known as Moericke traps. We hypothesized that the inclusion of innovative technologies, such as AI-powered insect pest monitoring using DYWTs leads to improved decision-making of crop protection measures for agricultural diversification strategies, resulting in optimized insect pest control methods without compromising OSR yield. This research aimed to (1) compare pollen beetle dynamics of DYWTs and YWTs in terms of counts; (2) evaluate the reliability of DYWTs' AI classification for pollen beetle immigration detection; and (3) use continuous monitoring data provided by the DYWT's AI to assess the impact of diversified landscapes and reduced insecticide applications on pollen beetle dynamics.

2. Materials and Methods

2.1 Study area

The study was conducted over three spring growing seasons (2020–21, 2021–22, 2022–23) in the landscape experiment patchCROP (52°27'05.4"N, 14°09'41.5"E). patchCROP was established in 2020 in Brandenburg, Northeastern Germany by the Leibniz Centre for Agricultural Landscape Research (ZALF). The landscape experiment was set up in a 70 ha field surrounded by 750 ha of agricultural fields. patchCROP is settled within an on-farm context in collaboration with the commercial farm Komturei Lietzen, who carried out all field management operations. In the main field, the dominant soil texture are loamy sands to sandy loams with 66% to 85% sand in the first 25 cm topsoil derived from glacial deposits. Average soil organic carbon content is low, ranging from 0.3% to 1.1% in the top 30 cm in May 2022. Soil pH varies from 5 to 7.3. The average yearly precipitation amounted to 460 mm, 616 mm, and 464 mm for the years 2020, 2021 and 2022, respectively. Daily maximum temperatures of 29.3°C were reached in July

2022 and daily lowest temperature of -9.4°C was measured in February 2021. Climatic data (supplementary Fig. S2) were obtained from two weather stations located in the eastern and western end of the main patchCROP field with a 15 min temporal resolution.

2.2 patchCROP landscape experiment and sampling design

The aim of patchCROP is to use temporal and spatial crop diversification to balance crop production with other ecosystem services and biodiversity while minimizing nutrient losses and pesticide applications. A main field akin to a checkerboard is the core of the patchCROP landscape experiment. Adjacent, commercial, sole-cropped fields serve as reference areas. The sole-cropped fields encompass a large area and are planted with only one crop per growing season. Sole-cropping is also called monoculture. As opposed to continuous monoculture or monocropping systems, where the same crop species is planted for consecutive seasons, sole-cropped fields undergo crop rotation.

Prior to the start of the landscape experiment, the main field of patchCROP was analysed for its heterogeneity regarding crop performance and soil properties; it was then divided into high-yield and low-yield potential zones using an advanced cluster analysis (Donat et al., 2022). Crops within the main field are planted in smaller, 0.5 ha (72 × 72 m) squares called "patches." In total, there are 30 patches across the main patchCROP field (Fig. 1). Their numeric identifiers range from 12 to 119 (e.g., Patch 12, Patch 74 etc). Each patch is subdivided into centrally located, permanent quadrants (18 × 18 m each) which facilitate sampling across different disciplines: biodiversity, soil, yield, and multipurpose, a mixed discipline area, used for more destructive sampling methods.

Throughout the main field, a crop is allotted three patches, each with a different management strategy: *Con, Red, Red + FS*. One of the patches, *Con*, has a conventional management strategy according to decisions made by the commercial farm ("business as usual"). Conventional decisions are based on IPM conducted by the farmer, who considers typical plant protection measures at the farm level. A second patch, *Red*, has a reduced management strategy. The reduced man-

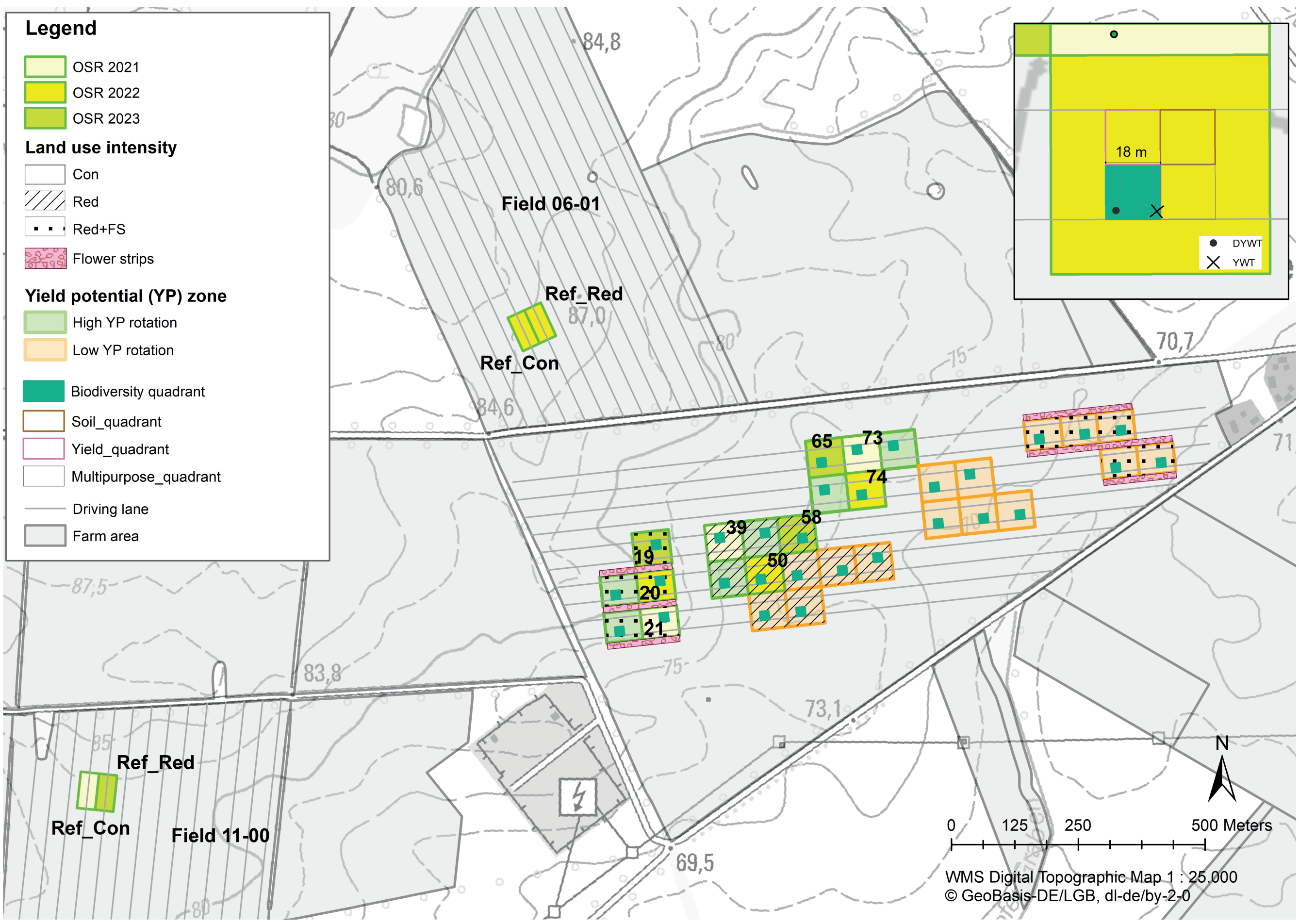

Fig. 1. Map of the patchCROP landscape experiment. patchCROP and the surrounding reference fields are shown. The location of the oilseed rape (OSR) patches and reference fields are highlighted to show the three harvest years (2021, 2022, 2023). Adjacent reference fields without OSR are not shown. Right corner: Close-up view of digital (DYWT) and yellow water trap (YWT) placement in a patch's biodiversity quadrant. In addition to containing the YWTs, the biodiversity quadrant is used for experiments and data collection related to biodiversity (e.g. capturing insects in pitfall traps). The soil quadrant is used for soil sampling and related experiments. The yield quadrant is used for taking biomass cuttings and other harvest related data collection. The multipurpose quadrant is used for data collection that is more destructive to the crop and would be detrimental to experiments in other quadrants. (Bar: Barley, CC: cover crops, Soy: soybean, Maiz: Maize, Whe: Wheat).

agement strategy uses optimized, situation-specific plant protection based strictly on control thresholds. Decisions are made based on precise, weekly monitoring and pest counts, and strict adherence to the results of forecasting models. The third patch, *Red + FS*, also follows the decision-making process of *Red* and pushes the treatment to later stages and/or the upper limits of pest infestation. *Red + FS* also potentially omits insecticide treatments to fully exploit the benefits of migrating antagonists from surrounding perennial flower strips (Table 1). The flower strips surrounding *Red + FS* patches are assumed to increase natural insect pest control, therefore further reducing insecticide needs (Tschumi et al., 2015). Sowing appropriate flower species, namely those with high UV reflectance, nectar availability, and a blooming time earlier to OSR, can further support parasitoid populations (Hatt et al., 2018). Since March 2021, monitoring and recommendations for *Red, Red + FS*, and *Ref_Red* have been carried out by researchers of the Julius Kühn Institute (JKI), the German Federal Research Centre for Cultivated Plants. Prior to March 2021, all patches received the same pesticide applications.

The large, adjacent sole-cropped fields are commercially managed. They are monitored to compare the effect of spatial diversification (field size) and temporal diversification (crop heterogeneity) (Fig. 1). Within each sole-cropped field is a 0.5 ha area divided into two halves. One half, *Ref_Con*, has a conventional management strategy comparable to the *Con* patch in patchCROP. The other half, *Ref_Red*, has a reduced management strategy comparable to the *Red* patch in patchCROP. The patch *Red + FS* has no counterpart in the sole-cropped, reference fields. Per year there is a single monitoring site for each of the five oilseed management strategies (Table 1): *Con, Red, Red + FS, Ref_Con, Ref_Red.*

For this study, data were collected annually during spring-summer in 2021, 2022, and 2023 across five OSR monitoring sites (Table 1, Fig. 1): three patches in patchCROP with diversified crop rotation (*Con*, *Red*, *Red + FS*) and two reference sites in a neighbouring, sole-cropped field (*Ref_Con*, *Ref_Red*) with narrow, business as usual crop rotation. patchCROP was designed with patches allotted to a high-yield potential zone or a low-yield potential zone. The two zones have a different five-year, legume-supported, crop rotation. OSR patches are located within the high-yield potential zone of patchCROP. The high-yield potential crop rotation includes OSR – winter barley – cover crops – soybean – cover crops – maize – winter wheat. The low yield crop rotation, although not studied here, is cover crops – sunflower – winter oats – cover crops – maize – lupin – winter rye. The reference fields have a different crop rotation than the patches. Field 11-00, the OSR reference for 2021 and 2023, had a previous crop rotation of wheat – maize – barely – OSR –barley –OSR. Field 06-01, the OSR reference for 2022, had a previous crop rotation of OSR – barley – cover crops – maize – wheat. Planting date, harvest date, and nitrogen (N) fertilizer dose were similar each year for the five OSR monitoring sites (Table 2). The OSR variety “Ambassador” was used in all years.

2.3 Data collection

2.3.1 Crop data

Yield was determined in the yield quadrant (18 × 18 m) of the patches using an experimental plot harvester in six sub-plots of 9 m length and 2 m cutting width (harvest area of 18 m^2). In the reference fields, yield was determined by harvesting six 20m^2 sub-plots in the central area of each reference. Yields were converted to 9% moisture level.

The treatment index (TI) was calculated for each monitoring site and year in relation to four plant protection categories: herbicides, insecticides, fungicides, and growth regulators (Roßberg et al., 2002). TI represents the number of pesticide applications in a farm area (e.g., a field), for a crop, or on a farm. TI considers reduced application rates and partial area treatments, where each pesticide product is counted separately in case of tank mixtures (BMEL, 2021). Until 2022, all TI numbers originated from the on-farm management software AGROCOM NET. Since 2023, the 365FarmNet software was used (last access date 11.07.2023). A detailed list of insecticide products by year, monitoring site, and concentration can be found in supplementary Table S1.

$$\text{Treatment index} = \sum_{1}^{n} \left(\frac{\text{applied application dose}}{\text{approved application dose}} x \, \frac{\text{treated area}}{\text{total area}} \right) \quad \text{(Equation 1)}$$

Table 1. Yearly locations of the five oilseed rape (OSR) monitoring sites. The sites change each year based on crop rotation. Each year, the monitoring sites are spread across three patches in the patchCROP landscape experiment (*Con*, *Red*, and *Red + FS)* and a reference area in a single field (*Ref_Con* and *Ref_Red)*. *Con* and *Ref_Con* are managed conventionally, following IPM practices according to EU directives. *Red* and *Ref_Red* are managed using a more rigorous IPM protocol determined by researchers at the Julius Kühn Institute. *Red + FS* also has a reduced management strategy and is additionally bordered by flower strips.

Abbreviation	Management strategy	Field type	Harvest Year		
			2021	2022	2023
Con	Conventional	*patchCROP*	Patch 73	Patch 74	Patch 65
Red	Reduced	*patchCROP*	Patch 39	Patch 50	Patch 58
Red + FS	Reduced + flower strip	*patchCROP*	Patch 21	Patch 20	Patch 19
Ref_Con	Conventional	*Reference field*	Field 11-00	Field 06-01	Field 11-00
Ref_Red	Reduced	*Reference field*			

Table 2. Field management information for oilseed rape (OSR) and intensity of pesticide application (Treatment index – TI) in the patchCROP landscape experiment. The table is reported by pesticide class (insecticides, herbicides, fungicides, growth regulators) and harvest year (2021, 2022 and 2023). The monitoring sites are separated based on their management strategies *Con*, *Red*, *Red + FS*, *Ref_Con*, and *Ref_Red*.

Harvest year	**2021**					**2022**					**2023**				
Monitoring site	*Con*	*Red*	*Red + FS*	*Ref_ Con*	*Ref_ Red*	*Con*	*Red*	*Red + FS*	*Ref_ Con*	*Ref_ Red*	*Con*	*Red*	*Red + FS*	*Ref_ Con*	*Ref_ Red*
Planting date	1-Sep-20					26-Aug-21					29-Aug-22				
Harvest date	23-Jul-21					20-Jul-22					24-Aug-23				
Fertilizer N (kg/ha)	161.4					148.4					153.0				
Treatment index of pesticide applications															
TI Insecticides	5.0	4.0	4.0	4.0	3.0	3.0	2.0	1.0	3.0	1.0	6.0	3.0	2.0	3.9	1.0
TI Herbicides	1.8	1.8	1.8	2.3	2.3	3.8	1.6	1.6	3.8	1.6	3.3	1.8	1.8	3.8	1.8
TI Fungicides	1.3	1.3	1.3	1.3	1.3	0.0	0.0	0.0	0.0	0.0	0.8	0.8	0.8	0.8	0.8
TI Growth regulators	1.1	0.6	0.6	1.3	0.8	1.0	0.6	0.6	1.0	0.6	1.7	0.4	0.4	1.5	0.4
TI Sum	9.2	7.7	7.7	8.9	7.4	7.8	4.2	3.2	7.8	3.2	11.8	6.0	5.0	10.0	4.0

2.3.2 Insect pest monitoring and taxonomic classification

In the patches, yellow water traps were installed exclusively in the biodiversity quadrant. In the reference monitoring sites, yellow water traps were installed along the driving lane. Two types of yellow water traps were installed. A conventional yellow water trap (YWT) was compared to a recently developed digital yellow water trap (DYWT) (Fig. 2). Both trap types were secured on a stick using zip ties and their height was increased as the crop developed. The yellow water traps were filled with water and a drop of dishwashing soap to en-

Fig. 2. Photographs of a yellow water trap (YWT) and a digital yellow water trap (DYWT) in an oilseed rape field. Note the solar power camera on top of the DYWT.

sure insect pest trapping. Trap contents were collected twice a week from stem elongation stage (BBCH 30) until development of pods (BBCH 70+).

The YWT had a circular shape with a diameter of 22 cm. It was covered by a plastic grid with gaps of approximately 1 cm × 1 cm to prevent the entry of larger insects. The DYWT was the MagicTrap recently released to the market by Bayer. The MagicTrap is the final iteration of a series of DYWT prototypes. It is square shaped, but otherwise shares a similar yellow colour, size, and grid size as the YWT. The MagicTrap is equipped with a battery-powered camera which can be recharged via USB-C cable or small, built-in solar-panels. The camera takes pictures at regular intervals throughout the day and then transfers the photos to Bayer's MagicScout application. Internet of things (IoT) coverage for the MagicScout is provided by the company 1NCE, which offers lifetime connectivity for low bandwidth devices. An AI model detects, classifies, and counts the insects in the trap. The AI identifies some insect pests at the species level, including the pollen beetle and the cabbage-stem flea beetle. Comparatively, the MagicTrap AI categorizes weevil species as a single group. The AI model also classifies, counts, and reports non-pest insect species as bycatch. Farmers can use the MagicScout app to receive updates about insect pest dynamics. Photos taken by the DYWT cameras were asynchronous with the manual collection times. Photos generally pre-date sample collection by a few hours and in some cases over 12 hours.

In 2021, one YWT was placed in each monitoring site (n=5). The *Con*, *Red + FS*, and *Ref_Con* sites were also equipped with DYWTs (n=3), totalling n=8 traps. In 2022, one YWT and one DYWT were placed in each monitoring site (YWT n=5 and DYWT n=5). After the validity of the DYWTs was established, only DYWTs were used in all five sites in 2023. Traps were positioned approximately one meter inside the driving lane to facilitate access later in the growing season and to ensure Internet connectivity. To reduce interference between the reference and digital traps, traps were positioned approximately 12 m apart from each other (Fig. 1).

Data collection was carried out every Monday and Thursday, when permitted by weather and safety protocols following pesticide applications. In 2021, monitoring took place from 07 April until 03 June 2021 (BBCH 35–73); however, DYWTs were not available until 10 May 2021 (BBCH 62). For 2022 and 2023, DYWTs were available the entire monitoring period from 21 March until 23 May 2022 (BBCH 31–75) and from 6 March until 22 May 2023 (BBCH 24–71). Both YWT and DYWT samples were brought from the field using plastic jars, manually classified, and then transferred to glass vials filled with 70% ethanol. In addition to pollen beetles, other prominent OSR insect pests were identified at the species level using guides by Martinez (2014) and Klausnitzer (2005). Their counts were used for IPM decision making but are not reported in this study.

In addition to yellow water traps, plant beating was conducted in every monitoring site. Plant beating results were used to verify if thresholds were exceeded for pollen beetles and to inform IPM decisions. Per site, 25 OSR plants underwent plant beating. In the patches, plant beating was carried out on five plants in the biodiversity, yield, and multipurpose sampling quadrants respectively, as well as five plants from each of the two driving lanes. In the reference sites, plant beating was carried out on 25 plants selected along the driving lane.

2.4 Data analyses

Data analyses involved three parts: (1) method comparison of the YWT and DYWT, (2) evaluation of the AI model's performance of classifying pollen beetles, and (3) analysis of pollen beetle dynamics affected by crop diversification at the landscape scale. All analyses were performed using R Statistical Software (v4.3.0; R Core Team 2023) in RStudio (v2023.3.1.446 "Cherry Blossom"; Rstudio Team, 2020). Visualizations were created using ggplot2 (v 3.4.2; Wickham, 2016) and Microsoft Excel.

2.4.1 Method validation of DYWT using Deming Regression

The manually determined pollen beetle counts from a YWT were compared to the manually determined DYWT counts from the same monitoring site and collection date. Pollen beetle counts from all sampling days and monitoring sites from 2021 (n=25) and 2022 (n=93) were aggregated into one data set for the method comparison analyses (total of n=118). Outliers were checked for. However, they were not removed, as they represented the immigration dynamics of pollen beetles into the rapeseed crop and were a result of natural fluctuations, not data collection error (Reuman et al., 2008).

The Shapiro-Wilk test determined that the YWT and DYWT count data were not normally distributed, so Spearman's rank correlation coefficient was used to test for correlation between the two traps. The Wilcoxon signed-rank test was then used to look for significant differences between the paired samples of YWT and DYWT counts. Lin's concordance correlation coefficient was used to establish the level of agreement between YWTs and DYWTs.

After finding a correlation between the two trap types, Deming regression was performed as a more robust method comparison analysis between YWTs and DYWTs using the mcr package (v1.3.2; Potapov et al., 2023). Unlike simple linear regression, which only accounts for error in the dependent variable, Deming regression accounts for error in both the reference variable, in this case YWTs, and the test variable, DYWTs (Ludbrook, 2010). The data were tested for heteroscedasticity using the Breusch-Pagan test ($p < .001$). Heteroscedasticity was present, so a weighted Deming regression was applied instead of a simple Deming regression (Bahar et al., 2017). Only positive integers can be included in a weighted Deming regression, so fewer YWT and DYWT pairs (n=72) were included. Confidence intervals were calculated using the jackknife (Linnet's) method with a confidence level of 95% (Linnet, 1993). Given that the measurement error (δ) is not established for yellow water traps, $\delta=1$ was used as default (Ellsäßer et al., 2021).

2.4.2 AI Evaluation with Confusion Matrices

The AI model's ability to classify pollen beetles was tested using DYWT samples from 2022 (n=93) and 2023 (n=97). Although DYWTs were used in 2021, they were not equipped with a camera and therefore had no associated AI model. Data from 2022 and 2023 were aggregated, then evaluated using confusion matrices generated via the caret package (v 6.0.94; Kuhn, 2008). A confusion matrix measures the performance of classification models in machine learning (Tharwat, 2018). It compares actual values to predicted values by calculating the true positives, false positives, true negatives, and false negatives produced by the AI model based on a binary classification (Tharwat, 2018). For this study, the actual value was the manually determined pollen beetle counts in a DYWT from a single date and monitoring site. The predicted value was the pollen beetle count according to the AI's classification for the same DYWT sample. The binary classification was based on a series of thresholds that represent possible severities of pollen beetle immigration or flight into the OSR crop: 5, 10, 15, 20, 25, 50, 75, 100, 125, 150, 200, 300, 400 and 500 pollen beetles.

A true positive (TP) occurs when the actual pollen beetle count and the predicted pollen beetle count both exceed the immigration threshold. A false positive (FP) occurs when the predicted value exceeds the immigration threshold, but the actual value does not. A true negative (TN) is when both the actual value and the predicted value are under the immigration threshold. A false negative (FN) occurs when the actual value exceeds the immigration threshold, but the predicted value does not.

From the confusion matrix (supplementary Fig. S3) generated for each threshold, five metrics were calculated which provided a more detailed overview of the AI model's performance: sensitivity, specificity, balanced accuracy, precision and F1 score. These metrics range from 0 to 1, where 0 represents the worst performance and 1 represents the best performance (Powers, 2007; Tharwat, 2018). Their calculations can be found in the supplementary information (Equations S1–S5).

2.4.3 Evaluating pollen beetle dynamics and crop performance in a diversified agricultural landscape

Pollen beetle dynamics and crop performance were assessed using general linear models (GLM) and simple correlation analysis. First, we used data from yellow water traps to assess the relationship between pollen beetle immigration, field size, and management strategies using GLMs. We then used GLMs to assess the relationship between yield, field size, and management strategies. Finally, we performed simple correlation tests to compare the dynamics of pollen beetle counts in yellow water traps to the pollen beetle counts from plant beating.

GLMs for pollen beetle dynamics were built in R using the MASS package (v7.3.58.4; Venables & Ripley, 2002). GLMs for yield were built using the stats package in R (v4.3.0; R Core Team 2023). We followed GLM guidelines suggested by Smith & Warren (2019). Pollen beetle count data from all three years was included and assumed the previously tested interchangeability between YWTs and DYWTs. In 2021, DYWTs were not used in all five monitoring sites, so the data (n=79) came from manually counted YWT samples. For 2022 (n=99) and 2023 (n=114), data came from the AI-classified DYWT samples.

For GLMs related to pollen beetle immigration, a Poisson model was selected because the response variable (adult pollen beetle abundance) was non-parametric count data. For visualizations of pollen beetle immigration dynamics, all data points were included. Overdispersion was present, so outliers (Z >3) were removed from the response variable and the data were refitted using a negative binomial model. For GLMs related to crop performance, a Gaussian model was selected, because the response variable (yield) was normally distributed. A full model that included all five monitoring sites was built. The full model included the type of the monitoring site (patch or field), management strategy (conventional, reduced, reduced + flower strip), year, and BBCH as fixed effects. The model failed to converge, so BBCH was removed. The model was incrementally tested using Akaike Information Criterion (AIC) scores to select the model with the best fit. The final model included type of the monitoring site, management strategy, and year. Two additional models were built to further analyse the response of pollen beetle dynamics on yield to field type. In these models, monitoring sites in the main patchCROP field (*Con* and *Red*) were compared to their counterparts in the reference field (*Ref_Con* and *Ref_Red*). The Mass and stats packages also calculated the significance of the GLM models.

For the simple correlation analysis between yellow water traps and plant beating, pollen beetle count data were aggregated from the inflorescence emergence stage (BBCH 50–60) in the years 2021, 2022, and 2023. Plant beating counts and yellow water trap counts from the same monitoring site and date were analysed together as a total of n=126 pairs. The Shapiro-Wilk test established that both the yellow trap and plant beating counts were not normally distributed ($p < 0.001$ for both methods), so the nonparametric Spearman's rank correlation rho was performed using the stats package in R (v4.3.0; R Core Team 2023).

3. Results

3.1 Method validation of DYWT

In 2021, YWTs (number of traps, n=3) and DYWTs (n=3) collected 1,110 and 1,218 pollen beetles, respectively. In 2022, YWTs (n=5) and DYWTs (n=5) collected 5,830 and 5,470 pollen beetles, respectively. Overall, the dynamics of pollen beetles in both YWTs and DYWTs followed the same pattern; however, variation existed. Based on the aggregated paired samples from spring 2021 and spring 2022 (n=118), Spearman's rank correlation rho suggests a strong, statistically significant relationship between the pollen beetle counts in YWT and DYWT (Table 3). Likewise, the Wilcoxon signed rank test with continuity correction showed no evidence for a systematic difference between YWT and DYWT. Lin's concordance correlation

Table 3. Statistical summary on method comparison between yellow water traps (YWT) and digital yellow water traps (DYWT).

YWT and DYWT pairs (n=118), aggregated from harvest years 2021 and 2022 pollen beetle counts	
Shapiro-Wilk YWT	p < 0.001
Shapiro-Wilk DYWT	p < 0.001
Spearman's rank correlation rho	rho = 0.84, p < 0.001
Wilcoxon signed rank	p = 0.884
Concordance correlation	0.94
Concordance correlation 95% confidence interval	0.91 – 0.96
Breusch-Pagan test	p < 0.001
YWT and DYWT pairs (n=72), aggregated from harvest years 2021 and 2022, only positive integer pairs	
Weighted Deming regression intercept	0.76
Weighted Deming regression slope	0.91 (n=72)
Intercept 95% confidence interval	-1.95 – 3.47
Slope 95% confidence interval	0.72 – 1.09
Spearman's rank correlation rho	rho = 0.76

coefficient suggests a moderate agreement between the two types of yellow water traps.

In the weighted Deming regression, the slope of the regression line (0.91) was just under the identity line (Fig. 3). The 95% confidence interval for slope (0.72–1.09) was around one, suggesting that there was no proportional systematic error between pollen beetle counts in YWT and DYWT. The intercept of the weighted Deming regression was positive (0.76) and the intercept 95% confidence interval (-1.95–3.47) contained zero, indicating there is no constant systematic error between the YWT and DYWT pollen beetle counts. Altogether, the manual and digital traps can be used interchangeably to assess pollen beetle dynamics and provide similar results.

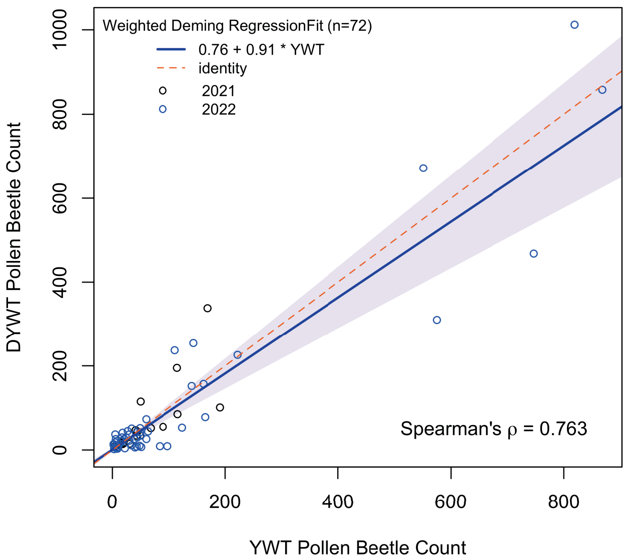

Fig. 3. Deming regression comparing YWT and DYWT pollen beetle counts. The 1:1 or identity line is for reference and the shaded cone is the confidence region. Data is aggregated from spring 2021 and spring 2022.

3.2 Evaluation of AI Model

The performance of the DYWT's AI model was evaluated using a gradient of pollen beetle immigration, ranging from a small number of beetles (n=5) to hundreds of beetles (n=500). Table 4 showcases the model's performance at different possible immigration severities, where the AI determined if the pollen beetle count was over or under the set threshold.

The AI model had very high sensitivity (0.98–1.00). From thresholds of 25 pollen beetles and higher, the AI model had perfect sensitivity. This suggests that the model is effective at correctly detecting when the immigration threshold is exceeded, especially at higher counts of pollen beetles. The AI model had moderate specificity for immigration thresholds under 100 pollen beetles (0.78–0.85). As the immigration threshold of pollen beetles increased, specificity generally performed worse. At the thresholds n= 100 and n=400, specificity was the lowest at only 0.50. The variation in specificity suggests variability in the AI model's ability to correctly determine true negatives (i.e., when the pollen beetle count is under the immigration threshold). Precision was high (0.89–0.98), suggesting that the model is generally capable of avoiding false positives. As the thresholds increased, precision also increased, resulting in a high ratio of true positives among all the predicted positive cases.

The balanced accuracy provides an average score of sensitivity and specificity. For thresholds between five and 75 pollen beetles, the balanced accuracy is high, ranging between 0.89 and 0.92. From thresholds of 100 pollen beetles and above, the balanced accuracy is lower, ranging from 0.75 to 0.83. This is due to the low specificity at higher thresholds. The F1 score, a combined metric of sensitivity and precision, ranged from 0.94–0.99. The higher the F1 score, the more balanced the model is between precision and sensitivity. This indicates that the AI model performed well regardless of the pollen beetle immigration threshold. Overall, the AI model performed very well in terms of sensitivity and precision.

Table 4. Confusion matrix metrics for the digital yellow water trap (DYWT) AI model.

Pollen beetle immigration threshold	Sensitivity (Recall)	Specificity	Precision	Balanced Accuracy	F1
n = 5	0.99	0.85	0.89	0.92	0.94
n = 10	0.98	0.82	0.91	0.90	0.94
n = 15	0.98	0.84	0.94	0.91	0.96
n = 20	0.99	0.82	0.94	0.91	0.97
n = 25	1.00	0.83	0.95	0.91	0.97
n = 50	1.00	0.79	0.97	0.90	0.99
n = 75	1.00	0.78	0.98	0.89	0.99
n = 100	1.00	0.50	0.96	0.75	0.98
n = 150	1.00	0.53	0.96	0.77	0.98
n = 200	1.00	0.57	0.97	0.79	0.98
n = 300	1.00	0.60	0.99	0.80	0.99
n = 400	1.00	0.50	0.99	0.75	0.99
n = 500	1.00	0.67	0.99	0.83	0.99

The variability in specificity suggests that the model could be improved for identifying negative cases, especially at higher immigration. Despite the variability, the AI model correctly determined when the pollen beetle counts exceeded various severity thresholds.

3.3 Pollen beetle dynamics and crop performance in a diversified agricultural landscape

Pollen beetle dynamics varied in both the temporal and spatial dimension. For the temporal dimension, the three years exhibited different patterns of pollen beetle dynamics (Fig. 4). According to the full model (Table 5), there were significant yearly differences. Pollen beetle abundance was highest in 2021, with lower pollen beetle abundance in 2022 and 2023. The management strategy did not have a statistically significant effect on adult pollen beetle abundance (Table 5). For the spatial dimension, pollen beetle counts were found to be higher in patch-sized monitoring sites when compared to field-sized monitoring sites (Table 5). When comparing the monitoring sites of the same management strategy, there was a marginally significant ($p < 0.1$) increase in pollen beetles for *Con* (Table 6) and a highly significant ($p = 0.001$) increase in pollen beetles for *Red* (Table 7) compared to their reference field counterparts *Ref_Con* and *Ref_Red*.

In 2021 (Fig. 4), pollen beetle abundance was notably higher in the three patches as compared to the reference sites. Insecticide was applied on 26 March (BBCH 28) to all monitoring sites (supplementary Table S1, 2020–2021) to control against rape stem weevils and cabbage stem weevils. There were four peaks in pollen beetle abundance on 22 April (BBCH 59), 29 April (BBCH 60), 10/13 May (BBCH 66/67), and 31 May (BBCH 72). Insecticides against pollen beetles were applied to *Con* and *Ref_Con* on 23 April. In 2022 (Fig. 4), pollen beetle dynamics were more similar across patches and reference sites. There was a prominent peak in pollen beetle immigration on 24 March (BBCH 50). Insecticides were applied on 26 March to control against rape stem weevils and cabbage stem weevils in all monitoring sites except *Ref_Red* (supplementary Table S1, 2021–2022). A second, less severe pollen beetle immigration occurred on 19 April (BBCH 59). No additional insecticides were applied for the remainder of the season. In 2023 (Fig. 4), there were more frequent but less pronounced peaks in pollen beetle abundance. The initial immigration occurred on 20 March (BBCH 32). Insecticide against rape stem weevils and cabbage stem weevils was applied on 22 March to the patches but to neither of the reference sites (supplementary Table S1, 2022–2023). The peak pollen beetle immigration happened on 24 April with a less severe immigration on 2 May (BBCH 64). On 26 April, insecticide to control pollen beetles was applied to *Con*, *Red* and *Ref_Con*. Insecticide to control brassica pod midges was applied on 8 May in *Con*.

Pollen beetle dynamics differed not only from year to year, but also between the yellow water traps and plant beating. Counts from both monitoring methods were compared during the inflorescence emergence stage (BBCH 50–60). Spearman's rank correlation rho suggested a statistically significant, moderate correlation ($rho = 0.46$, $p < 0.001$) between the pollen beetle counts in the yellow water traps and from plant beating. Notably, the relationship between the yellow water traps and plant beating varied from year to year, as demonstrated by the differing slopes of regression lines in Fig. 5 for 2021, 2022, and 2023. This underpins the loose relationship between pollen beetle immigration (yellow water traps) and crop infestation (plant beating), and thus damage.

OSR yield varied among management strategies, field sizes, and years. There were yearly fluctuations in OSR yields, with significantly higher yields in 2022 compared to 2021, and lowest in 2023 in all monitoring sites (supplementary Table S2). The lower yield in 2023 was caused by excessive rainfall in July (43.9 mm) and continuous rainfall events in August (47.5 mm until harvest on August 24). This caused delayed harvest and thus yield reduction, mainly due to shattering of pods, leading to average OSR yields of 2.59 t/ha compared to 3.67 and 4.2 t/ha in 2021 and 2022, respectively. For all cropping seasons, *Ref_Con* generally resulted in the highest OSR

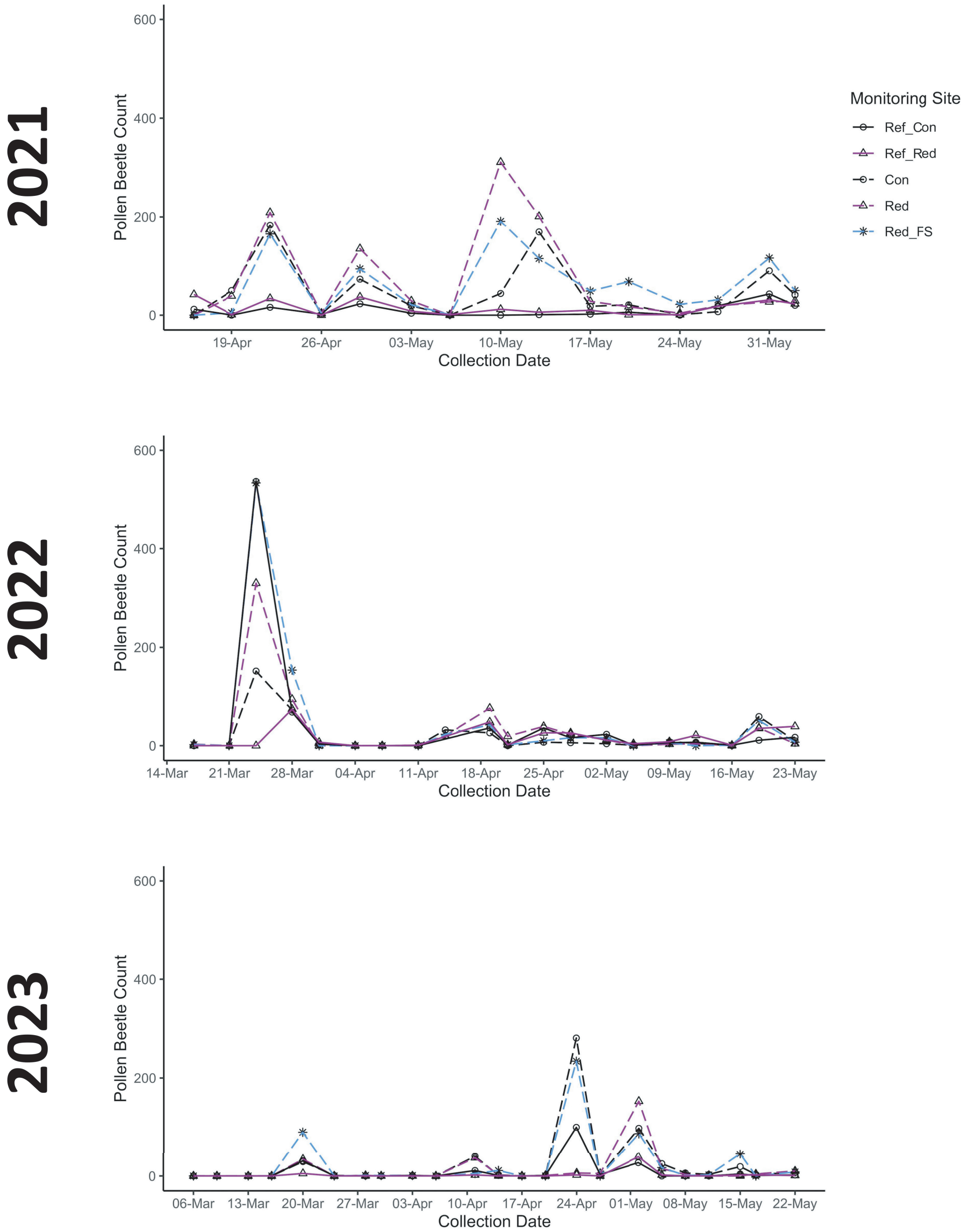

Fig. 4. Pollen beetle counts in yellow water traps from spring 2021, 2022, and 2023. Every monitoring site and collection date is included. Solid lines represent the sole-cropped reference fields and dashed lines represent patchCROP patches.

Table 5. All monitoring sites—Summary of negative binomial GLM to model the abundance of pollen beetles in response to monitoring site size (field or patch), management strategy (reduced, conventional, or reduced + flower strips), and collection year (2021, 2022, 2023).

Model Parameter	Estimate	SE	P
Intercept	3.04	0.29	< 0.001***
Monitoring site size (Reference: Field)			
Patch	0.74	0.26	0.001**
Management strategy (Reference: Conventional)			
Reduced	- 0.10	0.26	0.708
Reduced + Flower strip	0.04	0.34	0.896
Year (Reference: 2021)			
2022	- 0.62	0.30	0.01*
2023	- 1.34	0.29	< 0.001***

Table 6. Conventional monitoring sites—Summary of negative binomial GLM in monitoring sites with conventional management strategies. Models the abundance of pollen beetles in response to site size (patch or field) and collection year (2021, 2022, 2023).

Model Parameter	Estimate	SE	P
Intercept	2.85	0.40	< 0.001***
Monitoring site size (Reference: Field)			
Patch	0.67	0.37	0.071
Year (Reference: 2021)			
2022	- 0.44	0.48	0.364
2023	- 0.95	0.46	0.01*

Table 7. Reduced monitoring sites—Summary of negative binomial GLM in monitoring sites with reduced management strategies. Models the abundance of pollen beetles in response to site size (patch or field) and collection year (2021, 2022, 2023).

Model Parameter	Estimate	SE	P
Intercept	2.84	0.39	< 0.001***
Monitoring site size (Reference: Field)			
Patch	1.00	0.35	0.001**
Year (Reference: 2021)			
2022	- 0.43	0.46	0.353
2023	- 1.62	0.45	< 0.001***

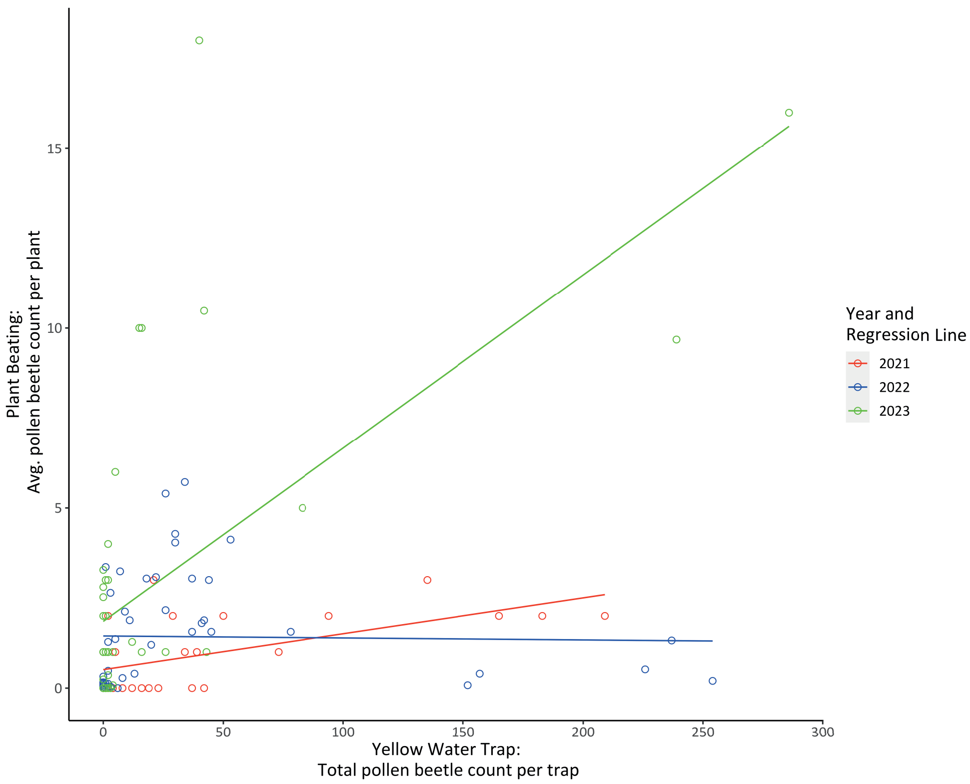

Fig. 5. Scatter plot comparing pollen beetle counts in yellow water traps versus pollen beetle counts from plant beating. Regression was not used to analyse the link between the two methods; however, regression lines are included on the scatter plot to better represent the relationship between yellow water traps and plant beating.

yields (Fig. 6). In 2021 and 2022, GLM showed lower average yields in the patches compared to yields in the reference fields (supplementary Tables S3–S10), but this difference was not observed in 2023 (supplementary Table S12). The effect of management strategies on OSR yield varied from year to year. In 2021, management strategies did not have a significant effect on yield in the full model (supplementary Table S3) or when analysing only the patches (supplementary Table S6). By contrast in 2022, differences existed between management strategies. GLM showed that the 2022 *Red* and *Red + FS* monitoring sites had slightly lower yields than monitoring sites with conventional management strategies (supplementary Table S7); however, when examining only the patches in 2022, there were no significant differences in OSR yield

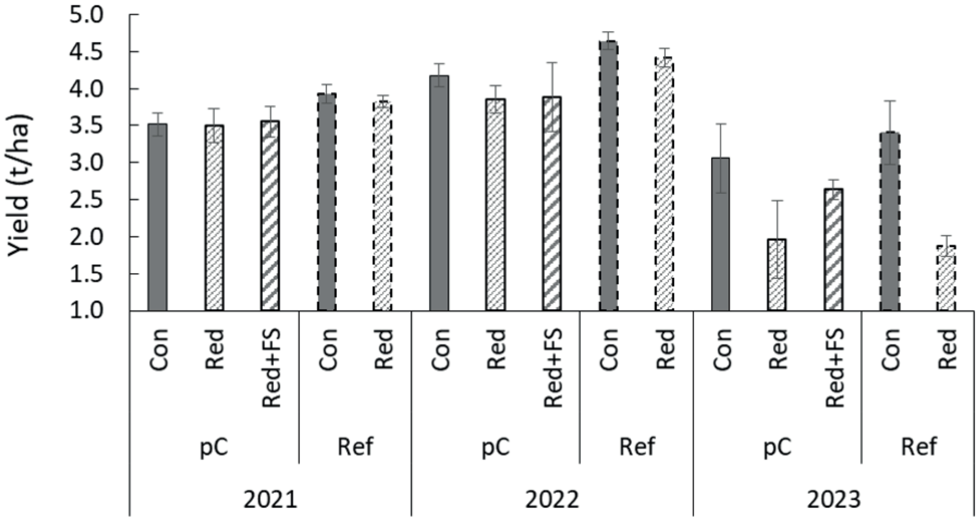

Fig. 6. Average oilseed rape (OSR) yield (in t/ha) for 2021, 2022, and 2023 and their respective monitoring sites. Conventional sites (Con) were managed with IPM practices according to EU directives. Reduced sites (Red) were monitored by researchers at the Julius Kühn Institute, who then provided more rigorous IPM recommendations. Sites bordered by flower strips (Red + FS) also had a reduced management strategy. Error bars indicate standard deviation. (pC: patch in the patchCROP landscape experiment, Ref: a sole-cropped, reference field).

regarding management strategies (supplementary Table S9). In 2023, assuming a similar disadvantage across monitoring sites due to delayed harvest, yield was significantly lower in *Red* and *Ref_Red* (Fig. 6) and highest in *Con* and *Ref_Con* (supplementary Table S11). Notably in the patches, *Red + FS* yields were only slightly lower than *Con* yields (supplementary Table S14).

The treatment index (TI) was calculated to classify the insecticide reduction potential without compromising yields (Fig. 7). In autumn 2020, all patches and references received identical pesticide applications. Starting in 2021, insecticide application was situation specific. Therefore, the differences in insecticide TI between monitoring sites was marginal, amounting only 20% less in reduced monitoring sites in the first cropping season. The use of insecticides was considerably lower in 2021/22, due to overall lower insect pest pressure and the implementation of reduction strategies from the beginning of the vegetation. In 2022/23, insect pest pressure was higher, causing a slight increase of overall insecticide use. However, insecticide usage remained at lower levels in the reduced monitoring sites than in the first year due to additional autumn insecticide reduction. By implementing a reduction approach where insecticide application was strictly situation dependent and not prophylactic, the TI of insecticides was reduced by over 50% over three years in the *Ref_Red* compared to *Ref_Con* monitoring site. Compared to *Con*, the insecticide TI was reduced by 35% in *Red* and 50% in *Red + FS*.

4. Discussion

The patchCROP landscape experiment was selected for this study to investigate diversified agricultural landscapes of the future (Pereponova et al., 2023). The hypothesis is, that through creating small-scale and site-specific cropping, we can reduce insect pest pressure on OSR and use digital technologies to monitor their dynamics. For the study, newly developed DYWTs were validated and then used to provide high-resolution, continuous pollen beetle monitoring. Different field sizes (small-scale diversified patches vs. large-scale, sole-cropped reference fields) and land use intensities were found to have trade-offs in pest dynamics and crop yields.

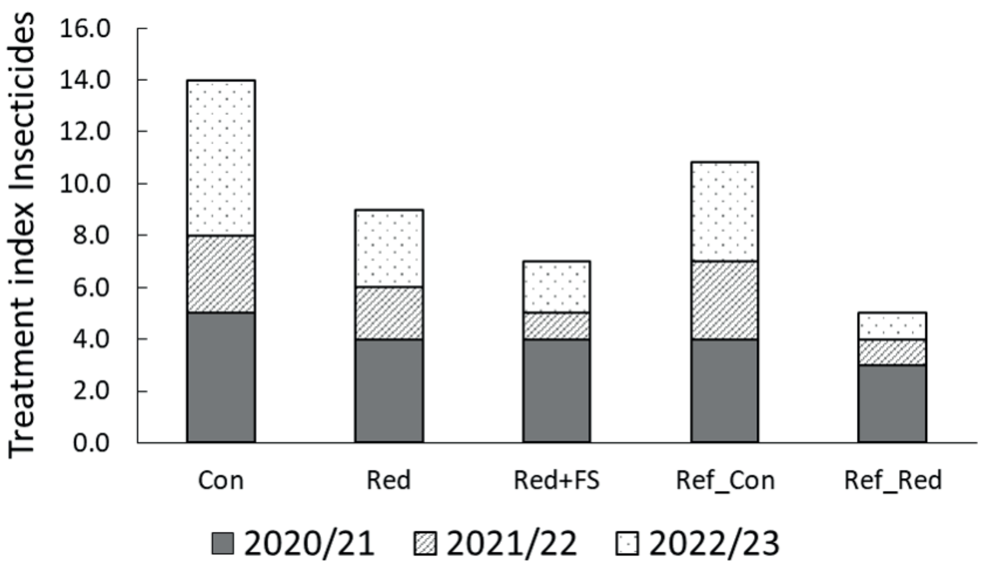

Fig. 7: The treatment index (TI) describes the intensity of insecticide applications per growing season and management strategy. In the 2021/22 growing season, the intensity of insecticide treatments in all management strategies was lower than in the 2020/21 and 2022/23 growing seasons. (in patchCROP: Con: conventional, Red: reduced, Red + FS: reduced + flower strips; in Reference fields: Ref_Con: conventional, Ref_Red: reduced)

4.1 Validation of DYWT

Despite some daily variation between the pollen beetle counts in YWTs and DYWTs, the overall patterns of pollen beetle dynamics in both yellow water trap types were very similar. The method validation of the yellow water traps demonstrated a satisfactory trapping efficacy with DYWT and a statistically proven interchangeability between pollen beetle counts obtained from YWTs and DYWTs, both of which are aspects to be considered successful camera traps (Preti et al., 2021). The daily variation between counts in YWTs versus DYWTs may be due to the highly mobile nature of pollen beetles. To find preferred resources, pollen beetles move not only from field to field, but also from plant to plant (Seimandi-Corda et al., 2021). Previous studies have also found that pollen beetles are not homogenously distributed across fields. Following immigration into OSR via anemotaxis (Skellern et al., 2017), early aggregation of pollen beetles often occurs upwind, also via anemotaxis, meaning that the pollen beetles cluster downwind of prevailing winds (Bick et al., 2023). Pollen beetles were also found to aggregate first at field edges during inflorescence development (BBCH 55–59) and then more centrally during flowering (Bick et al., 2023). Given that the YWTs and DYWTs were spaced 12 m apart, the difference in YWT and DYWT counts is likely not a methodological difference between the devices. Instead, the discrepancies could be explained by spatial variability of pollen beetles, prevailing winds, tendency to cluster at edges and then the centre of fields, and possible preference for available food sources in the vicinity of the yellow water traps. Overall, the results suggest that DYWTs are a viable and accurate means of monitoring pollen beetle immigration dynamics in diversified agricultural landscapes.

4.2 Validation of AI

After validating the DYWTs as a suitable methodology for monitoring the immigration dynamics of pollen beetles, we validated the performance of the AI model. The evaluation of the AI model demonstrated its effectiveness at classifying pollen beetles based on immigration severities ranging from five to 500 pollen beetles. The AI model exhibited high sensitivity and precision, especially at higher pollen beetle immigration severities, indicating that the model could correctly detect when the pollen beetle count in a DYWT exceeded a pre-established severity. The high F1-score further indicates that the AI model is a very good classifier (Bjerge et al., 2023; Mendoza et al., 2023), because it could detect and properly classify a range of pollen beetle immigration dynamics. These are important criteria for the timely and precise monitoring of insect pests, as well as for sending farmers reminders to visit traps (Rosado et al., 2022), thus showing that the AI model in the commercial DYWT is a valuable support tool for targeted pest management interventions.

Future research directions may involve expanding AI-powered pest monitoring to species in crops other than OSR (Cardim Ferreira Lima et al., 2020), allowing for a more comprehensive assessment of pest dynamics in diversified cropping systems. Integrating real-time environmental data, such as including temperature sensors near each trap, could further improve the information sent to farmers by the DYWT (Rosado et al., 2022). The commercial DYWT is regularly retrained to better identify insect pests and improve its performance using pictures obtained from each cropping season. Further training of its taxonomic classification abilities and integrating deep learning (Christin et al., 2019; He et al., 2019) could provide valuable insights into the factors influencing insect pest population dynamics or may improve regional prediction through decision support systems.

4.3 Pollen beetle dynamics in a diversified landscape setting

In our study, the patches in diversified settings had higher pest pressure and lower average OSR yields compared to larger, sole-cropped fields. However, when comparing yields among the patches, there was not a consistently large difference in yields between the *Con*, *Red*, and *Red + FS* monitoring sites. When compared to *Con* insecticide applications and yields, reduced insecticide applications in *Red* and *Red + FS* (Table 2) did not lead to a significant yield decrease (Fig. 6) in 2021 or 2022, or for *Red + FS* in 2023. The timely insecticide applications by weekly expert decisions likely helped keep yield losses to a minimum. Intensive insect pest monitoring in *Red* and *Red + FS* monitoring sites prevented insecticide spraying.

Various beneficial interactions arising from crop diversification with smaller field size may have contributed to enhanced crop resilience in *Red + FS* and partly in *Red*. For example, the strong interaction of insect pollination, insect density, and insect diversity, and as well as the diversified field conditions (Ouvrard & Jacquemart, 2019) present in *Red + FS* could have benefited yields without the spraying of additional insecticides. Given that conventional methods of spraying insecticides have been shown to reduce pollen beetle parasitism (Hausmann et al., 2021), the reduced amounts of insecticides in *Red + FS* might have accelerated biological control of pollen beetles by their parasitoids. Furthermore, OSR is an insect-pollinated crop, so reduced insecticide usage potentially offset the negative effects of smaller field sizes via improved pollination, thus outweighing yield loss (Perrot et al., 2018). Flower strips, which have been reported to enhance pollen beetle parasitism (Krimmer et al., 2022), could have also led to effective natural control of insect pests in *Red + FS*. In the future, if flower mixtures that appeal to OSR parasitoids are planted, the benefits of flower strips could be further enhanced (Hatt et al., 2018). Finally, *Red + FS* sites were closest to coppices along the patchCROP border. The more diverse landscape offered by trees and bushes may have fostered a greater parasitism rate compared to the other sites (Veromann et al., 2009), which were located farther from wooded areas.

In terms of pest dynamics, pollen beetles are highly mobile, and their immigration is more likely in areas with higher infestation, whereas in areas with comparatively higher insecticide applications, their abundance is lower (Rusch et al., 2011). This discrepancy might also explain why *Ref_Red* had overall lower pollen beetle counts in the yellow water traps than its patch counterpart *Red*. The insect pest pressure in *Ref_Red* was possibly reduced by its conventional surroundings. Because the entire reference field surrounding *Ref_Red* was managed with insecticides, a comparability to reduced patches is limited and a pest dilution effect was assumed. Overall, the interactions which govern real, working agroecosystems are highly complex. Although these interactions are challenging to disentangle at the landscape level, this study was able to elucidate interactions among various landscape structures and insecticide reduction approaches, not only in terms of biodiversity, but also for productivity and feasibility.

In Germany, there are no established insecticide application thresholds for pollen beetles found in YWTs. The indication to apply insecticides against pollen beetles is determined by the plant beating counts (Bartels et al., 2023; Freier et al., 2018). YWTs serve as a warning device to notify farmers of the immigration of pollen beetles. When pollen beetles are discovered in YWTs, farmers should perform plant beating to determine damage thresholds. Our findings are a larger scale field experiment which support those of Metspalu et al. (2015), who concluded that YWTs are a good indicator of pollen beetle movement and long-term continuous monitoring, whereas plant beating is more suitable for rapid monitoring and decision making, such as determining pollen beetle thresholds in OSR. Although the DYWT AI can correctly alert farmers about pollen beetle immigration, the final decision to apply insecticide should still be indicated by the established pollen beetle thresholds from plant beating, not the pollen beetle count in the yellow water traps.

The implementation of digital yellow water traps (DYWTs) represents a significant advancement in the technical dimension of agricultural landscape monitoring. These traps offer high-resolution data, which facilities continuous monitoring of pollen beetles (Metspalu et al., 2015) and helps farmer improve targeted control. Importantly, by looking at the photographs and insect pest summary provided by the associated phone application, farmers can limit the time spent in the field checking for pollen beetle immigration. Instead, farmers can use DYWTs as an alert system for pollen beetle immigration and prioritize their time doing plant beating when necessary. This combination allows OSR farmers to achieve the ecological benefits of adhering to insect pest thresholds and the principles of IPM while incurring a lower cost of labour (Thiel et al., 2023). The combination of farm-relevant data and pest management decision-making alongside the promotion of ecosystem services for biological pest control make DYWTs a suitable tool for IPM (Schellhorn et al., 2015). A well-informed IPM decision might ultimately result in the omission of insecticide treatments. If insecticide is deemed necessary under IPM, the choice of an appropriate insecticide to control OSR insect pests in spring is foremost led by issues of resistance management (changing modes of action) and considerations of the least side effects for beneficial insects. The limited number of authorised insecticides underscores the need of monitoring and adherence to threshold values prior to insecticide treatments.

Ideally, a constellation of different data types would be considered in future IPM methodologies. For example, habitat characteristics like relative altitude, litter (crop residue) thickness, soil moisture, and proximity to the previous year's OSR fields at both local and landscape scale would also be included, as they contribute to pollen beetle abundance and should be considered for IPM (Rusch et al., 2012). Additionally, meteorological data, especially temperature and wind speed, would be incorporated to better predict the abundance of pollen beetle immigration (Skellern et al., 2017). Using conventional insect pest monitoring methods, the inclusion of all these observations is hardly feasible; however, future technologies will hopefully allow seamless integration of all relevant insect pest monitoring data.

5. Conclusion

The successful validation of DYWTs and the performance of the AI model confirm their suitability as tools for continuous monitoring of pollen beetle immigration in diversified agricultural landscapes. The combination of DYWTs and AI image classification packaged into a smartphone application is an efficient and human-centred technology. These innovative technologies can support farmers in the rigorous monitoring of pollen beetles, while simultaneously reducing the labour-intensive nature of conventional insect pest monitoring methods. The DYWTs provide accurate, timely information which can help farmers know when to go to the field and perform plant beating to determine pollen beetle thresholds. Whereas DYWTs serve in identifying insect pest trends and patterns, plant beating can give a clearer indication of current pollen beetle infestation. When used together, the two methods are powerful tools for pollen beetle monitoring in OSR and have the potential to support more specific, targeted applications of insecticides.

Although DYWTs were useful tools for pollen beetle monitoring, we reject the hypothesis that agricultural diversification through patch-cropping resulted in lower pesticide application without compromising OSR yields. Over three harvest years, OSR yield was lower in the smaller sized patches compared to large fields, although this discrepancy was less expressed in monitoring sites with conventional pest management. Notably, we found that the situation specific insecticide reduction was not the most relevant controlling yield factor for monitoring sites in 2021 and 2023, nor in the patches in both 2021 and 2022. This proves the validity of the concept of thresholds and suggests that farmers can rely on threshold values, which with their rigorous application contributes to reduce pesticide applications without compromising OSR yield in smaller fields. Perennial flower strips showed their potential in playing an important role in regulating pollen beetle dynamics in smaller fields. Integrating DYWTs with additional data sources and more sophisticated AI could further illuminate the complex interactions between insect pest dynamics, crop performance, and diversification strategies. Researchers could use this robust knowledge in changing crop mosaics and semi-natural habitats to develop sustainable pest management strategies.

Acknowledgement

We thank Max Alexander Rettig, Robert Zieciak, and Felix Erbe for the support in field data collection. We acknowledge Sigrid Ehlert for the visualisation of the experimental design.

The maintenance of the patchCROP infrastructure is supported by the Leibniz Centre for Agricultural Landscape Research. The authors acknowledge support from Julius Kühn Institute and the German Research Foundation under Germany's Excellence Strategy, EXC-2070-390732324-PhenoRob. The yellow traps, both YWTs and DYWTs, were provided free of charge by Bayer AG. We greatly appreciate the possibility to conduct on-farm experimentation with the project partner Komturei Lietzen GmbH. We thank the anonymous reviewers for their careful reading of our manuscript and their many insightful comments and suggestions.

Conflicts of interest

The authors declare that they do not have any conflicts of interest.

Data availability

The data that support the findings of this study are available from the corresponding author, KG, upon request.

References

Arthey, T., 2020: Challenges and Perspectives in Global Rapeseed Production. agri benchmark, 1–43, URL: http://www.agribenchmark.org/cash-crop/publications-and-projects0/reports/challenges-and-perspectives-in-global-rapeseed-production.html.

Bahar, B., Tuncel, A.F., Holmes, E.W., & Holmes, D.T., 2017: An interactive website for analytical method comparison and bias estimation. Clinical Biochemistry 50 (18), 1025–1029, DOI: 10.1016/j.clinbiochem.2017.08.008.

Bartels, A., Haberlah-Korr, V., Schäfer, B.C., 2023: Leitlinie des integrierten Pflanzenschutzes im Rapsanbau. URL: https://www.ufop.de/.

Bick, E., Sigsgaard, L., Torrance, M.T., Helmreich, S., Still, L., Beck, B., Rashid, R.E., Lemmich, J., Nikolajsen, T., Cook, S.M., 2023: Dynamics of pollen beetle (*Brassicogethes aeneus*) immigration and colonization of oilseed rape (*Brassica napus*) in Europe. Pest Management Science, 1-8, DOI: 10.1002/ps.7538.

Bjerge, K., Alison, J., Dyrmann, M., Frigaard, C.E., Mann, H.M.R., Høye, T.T, 2023: Accurate detection and identification of insects from camera trap images with deep learning. PLOS Sustainability and Transformation 2 (3), 1–18, DOI: 10.1371/journal.pstr.0000051.

BMEL., 2021: Jahresbericht 2021 des NAP Pflanzenschutz: Nationaler Aktionsplan zur nachhaltigen Anwendung von Pflanzenschutzmitteln, 1–76, URL: https://www.bmel.de/.

Busse, M., Zoll, F., Siebert, R., Bartels, A., Bokelmann, A., Scharschmidt, P., 2021: How farmers think about insects: perceptions of biodiversity, biodiversity loss and attitudes towards insect-friendly farming practices. Biodiversity and Conservation 30 (11), 3045–3066, DOI: 10.1007/s10531-021-02235-2.

Cardim Ferreira Lima, M., Damascena de Almeida Leandro, M.E., Valero, C., Pereira Coronel, L.C., Gonçalves Bazzo, C.O, 2020: Automatic detection and monitoring of insect pests—A review. Agriculture (Switzerland) 10 (5), 1-24, DOI: 10.3390/agriculture10050161.

Christin, S., Hervet, É., Lecomte, N., 2019: Applications for deep learning in ecology. British Ecological Society: Methods in Ecology and Evolution 10 (10), 1632–1644, DOI: 10.1111/2041-210X.13256.

Daum, E., Brandes, M., Heimbach, U., Zimmer, C., Slater, R., Elias, J., 2023: Frequency and spatial distribution of knockdown resistance (kdr) to pyrethroids in multiple oilseed rape pest species of the genus *Ceutorhynchus*. Pest Management Science. DOI: 10.1002/ps.7549.

Donat, M., Geistert, J., Grahmann, K., Bloch, R., Bellingrath-Kimura, S.D., 2022: Patch cropping- a new methodological approach to determine new field arrangements that increase the multifunctionality of agricultural landscapes. Computers and Electronics in Agriculture 197, 1–15, DOI: 10.1016/j.compag.2022.106894.

Döring, T.F., Skellern, M., Watts, N., Cook, S, 2012: Colour choice behaviour in the pollen beetle *Meligethes aeneus* (Coleoptera: Nitidulidae). Physiological Entomology 37 (4), 360–378, DOI: 10.1111/j.1365-3032.2012.00850.x.

Ellsäßer, F., Stiegler, C., Röll, A., June, T., Knohl, A., Hölscher, D, 2021: Predicting evapotranspiration from drone-based thermography – a method comparison in a tropical oil palm plantation. Biogeosciences 18 (3), 861–872, DOI: 10.5194/bg-18-861-2021.

Freier, B., Gummert, A., Klocke, B., Schwarz, J., Dachbrodt-Saaydeh, S., Krengel, S., Kehlenbeck, H., 2018: Integrierter Pflanzenschutz (Eiden, H.C., W. Henke, V. Bräutigam, Planer, J. (eds.), 7th ed., MKL Druck GmbH Co.

Haan, N.L., Zhang, Y., Landis, D.A., 2020: Predicting Landscape Configuration Effects on Agricultural Pest Suppression. Trends in Ecology and Evolution 35 (2), 175–186, DOI: 10.1016/j.tree.2019.10.003.

Habel, J.C., Samways, M.J., Schmitt, T., 2019: Mitigating the precipitous decline of terrestrial European insects: Requirements for a new strategy. Biodiversity and Conservation 28, 1343–1360, DOI: 10.1007/s10531-019-01741-8.

Hatt, S., Uyttenbroeck, R., Lopes, T., Chen, J.L., Piqueray, J., Monty, A., Francis, F., 2018: Effect of flower traits and hosts on the abundance of parasitoids in perennial multiple species wildflower strips sown within oilseed rape (*Brassica napus*) crops. Arthropod-Plant Interactions 12, 787–797, DOI: 10.1007/s11829-017-9567-8.

Hausmann, J., Heimbach, U., Rostás, M., Brandes, M., 2021: The effect of insecticide application by dropleg sprayers on pollen beetle parasitism in oilseed rape. BioControl 66, 765-777, DOI: 10.1007/s10526-021-10111-9.

He, Y., Zeng, H., Fan, Y., Ji, S., Wu, J., 2019: Application of Deep Learning in Integrated Pest Management: A Real-Time System for Detection and Diagnosis of Oilseed Rape Pests. Mobile Information Systems 2019, 1–14, DOI: 10.1155/2019/4570808.

Heimbach, U., Müller, A., 2012: Incidence of pyrethroid-resistant oilseed rape pests in Germany. Pest Management Science 69 (2), 209–216, DOI: 10.1002/ps.3351.

Klausnitzer, B., 2005: Exkursionsfauna von Deutschland: Band 2 Wirbellose: Insekten. Spektrum Akademischer Verlag.

Krimmer, E., Martin, E.A., Holzschuh, A., Krauss, J., Steffan-Dewenter, I., 2022: Flower fields and pesticide use interactively shape pollen beetle infestation and parasitism in oilseed rape fields. Journal of Applied Ecology 59 (1), 263–273, DOI: 10.1111/1365-2664.14051.

Kuhn, M., 2008: Building Predictive Models in R Using the caret Package. Journal of Statistical Software 28 (5), 1–26, DOI: 10.18637/jss.v028.i05.

Landis, D.A., 2017: Designing agricultural landscapes for biodiversity-based ecosystem services. Basic and Applied Ecology 18, 1–12, DOI: 10.1016/j.baae.2016.07.005.

Linnet, K., 1993: Evaluation of regression procedures for methods comparison studies. Clinical Chemistry 39 (3), 424–432, DOI: 10.1093/clinchem/39.3.424.

Ludbrook, J., 2010: Linear regression analysis for comparing two measurers or methods of measurement: But which regression? Clinical and Experimental Pharmacology and Physiology 37 (7), 692–699, DOI: 10.1111/j.1440-1681.2010.05376.x.

Lundin, O., 2021: Consequences of the neonicotinoid seed treatment ban on oilseed rape production – what can be learnt from the Swedish experience? Pest Management Science 77 (9), 3815–3819, DOI: 10.1002/ps.6361.

Martinez, O., 2014: Steckbriefe Rapsschädlinge. Dienstleistungszentrum Ländlicher Raum Rheinhessen-Nahe-Hunsrück.

Mendoza, Q.A., Pordesimo, L., Neilsen, M., Armstrong, P., Campbell, J., Mendoza, P.T., 2023: Application of Machine Learning for Insect Monitoring in Grain Facilities. AI 4 (1), 348–360, DOI: 10.3390/ai4010017.

Metspalu, L., Veromann, E., Kaasik, R., Kovacs, G., Williams, I.H., Mänd, M., 2015: Comparison of sampling methods for estimating the abundance of *Meligethes aeneus* on oilseed crops, International Journal of Pest Management 61 (4), 312–319, DOI: 10.1080/09670874.2015.1058992.

Montgomery, G.A., Belitz, M.W., Guralnick, R.P., Tingley, M.W., 2021: Standards and Best Practices for Monitoring and Benchmarking Insects. Frontiers in Ecology and Evolution 8, 1–18, DOI: 10.3389/fevo.2020.579193.

Ortega-Ramos, P.A., Mauchline, A.L., Metcalfe, H., Cook, S.M., Girling, R.D., Collins, L., 2023: Modelling the factors affecting the spatiotemporal distribution of cabbage stem flea beetle (*Psylliodes chrysocephala*) larvae in winter oilseed rape (*Brassica napus*) in the UK. Pest Management Science, 1–15, DOI: 10.1002/ps.7427.

Ouvrard, P., Jacquemart, A.L., 2019: Review of methods to investigate pollinator dependency in oilseed rape (*Brassica napus*). Field Crops Research 231, 18–29, DOI: 10.1016/j.fcr.2018.11.006.

Pereponova, A., Grahmann, K., Lischeid, G., Bellingrath-Kimura, S.D., Ewert, F., 2023: Sustainable transformation of agriculture requires landscape experiments. Heliyon 9 (11), 1–16. DOI: 10.1016/j.heliyon.2023.e21215.

Perrot, T., Gaba, S., Roncoroni, M., Gautier, J.-L., Bretagnolle, V., 2018: Bees increase oilseed rape yield under real field conditions. Agriculture, Ecosystems & Environment 266, 39–48, DOI: 10.1016/j.agee.2018.07.020.

Potapov, S., Model, F., Schuetzenmeister, A., Manuilova, E., Dufey, F., Raymaekers, J., 2023: _mcr: Method Comparison Regression_. R package version 1.3.2. URL: https://CRAN.R-project.org/package=mcr.

Powers, D.M.W., 2007: Evaluation: From Precision, Recall and F-Factor to ROC, Informedness, Markedness & Correlation. International Journal of Machine Learning Technology 2 (1), 37–63, DOI: 10.48550/arXiv.2010.16061.

Preti, M., Verheggen, F., Angeli, S., 2021: Insect pest monitoring with camera-equipped traps: strengths and limitations. Journal of Pest Science 94 (2), 203–217, DOI: doi.org/10.1007/s10340-020-01309-4.

R Core Team, 2023: _R: A Language and Environment for Statistical Computing_. R Foundation for Statistical Computing, Vienna, Austria. URL: https://www.R-project.org/.

RStudio Team, 2020: RStudio: Integrated Development for R. RStudio, PBC, Boston, MA. URL: http://www.rstudio.com/.

Reuman, D.C., Costantino, R.F., Desharnais, R.A., Cohen, J.E., 2008: Colour of environmental noise affects the nonlinear dynamics of cycling, stage-structured populations. Ecology Letters 11 (8), 820–830, DOI: 10.1111/j.1461-0248.2008.01194.x.

Rosado, L., Faria, P., Gonçalves, J., Silva, E., Vasconcelos, A., Braga, C., Oliveira, J., Gomes, R., Barbosa, T., Ribeiro, D., Nogueira, T., Ferreira, A., Carlos, C., 2022: EyesOnTraps: AI-Powered Mobile-Based Solution for Pest Monitoring in Viticulture. Sustainability (Switzerland) 14 (15), 9729, DOI: 10.3390/su14159729.

Roßberg, D., Gutsche, V., Enzian, S., Wick, M., 2002: Neptun 2000 – Erhebung von Daten zum tatsächlichen Einsatz chemischer Pflanzenschutzmittel im Ackerbau Deutschlands. Berichte aus der Biologischen Bundesanstalt für Land- und Forstwirtschaft (BBA).

Rusch, A., Valantin-Morison, M., Roger-Estrade, J., Sarthou, J.P., 2012: Local and landscape determinants of pollen beetle abundance in overwintering habitats. Agricultural and Forest Entomology 14 (1), 37–47, DOI: 10.1111/j.1461-9563.2011.00547.x.

Rusch, A., Valantin-Morison, M., Sarthou, J.-P., Roger-Estrade, J., 2011: Multi-scale effects of landscape complexity and crop management on pollen beetle parasitism rate. Landscape Ecology 26 (4), 473–486, DOI: 10.1007/s10980-011-9573-7.

Schellhorn, N.A., Parry, H.R., Macfadyen, S., Wang, Y., Zalucki, M.P., 2015: Connecting scales: Achieving in-field pest control from areawide and landscape ecology studies. Insect Science 22 (1), 35–51, DOI: 10.1111/1744-7917.12161.

Seimandi-Corda, G., Jenkins, T., Cook, S.M., 2021: Sampling pollen beetle (*Brassicogethes aeneus*) pressure in oilseed rape: which method is best? Pest Management Science 77 (6), 2785–2794, DOI: 10.1002/ps.6310.

Shortall, C.R., Cook, S.M, Mauchline, A.L., Bell, J.R., 2023: Long-term trends in migrating *Brassicogethes aeneus* in the UK. Pest Management Science, 1–12, DOI: 10.1002/ps.7501.

Sirami, C., Gross, N., Baillod, A.B., Bertrand, C., Carrié, R., Hass, A., Henckel, L., Miguet, P., Vuillot, C., Alignier, A., Girard, J., Batáry, P., Clough, Y., Violle, C., Giralt, D., Bota, G., Badenhausser, I., Lefebvre, G., Gauffre, B., Vialatte, A. et al., 2019: Increasing crop heterogeneity enhances multitrophic diversity across agricultural regions. Proceedings of the National Academy of Sciences of the United States of America, 116 (33), 16442–16447, DOI: 10.1073/pnas.1906419116.

Skellern, M.P, Welham, S.J., Watts, N.P., Cook, S.M., 2017: Meteorological and landscape influences on pollen beetle immigration into oilseed rape crops. Agriculture, Ecosystems and Environment (241), 150–159, DOI: 10.1016/j.agee.2017.03.008.

Smith, C., Warren, M., 2019: GLMs in R for Ecology. 79 pp., ISBN: 978-1089681878.

Tamburini, G., Bommarco, R., Cherico Wanger, T., Kremen, C., Van Der Heijden, M.G.A., Liebman, M., Hallin, S., 2020: Agricultural diversification promotes multiple ecosystem services without compromising yield. Science Advances 6 (45), 1–8, DOI: 10.1126/sciadv.aba1715.

Tharwat, A., 2018: Classification assessment methods. Applied Computing and Informatics 17 (1), 168–192, DOI: 10.1016/j.aci.2018.08.003.

Thiel, L., Mergenthaler, M., Wutke, M., Haberlah-Korr, V., 2023: Use of insect pest thresholds in oilseed rape and cereals: is it worth it? Pest Management Science, 1–9, DOI: 10.1002/ps.764.

Tschumi, M., Albrecht, M., Entling, M.H., Jacot, K., 2015: High effectiveness of tailored flower strips in reducing pests and crop plant damage. Proceedings of the Royal Society B: Biological Sciences 282 (1814), 1–8, DOI: 10.1098/rspb.2015.1369.

Venables, W.N. Ripley, B.D., 2002: Modern Applied Statistics with S. Fourth Edition. Springer, New York. ISBN: 0-387-95457-0.

Veromann, E., Saarniit, M., Kevväi, R., Luik, A., 2009: Effect of crop management on the incidence of *Meligethes aeneus* Fab. and their larval parasitism rate in organic and conventional winter oilseed rape. Agronomy Research (7), 548–554.

Vinnichek, L., Pogorelova, E., & Dergunov, A., 2019: Oilseed market: Global trends. IOP Conference Series: Earth and Environmental Science 274 (1), 1–5, DOI: 10.1088/1755-1315/274/1/012030.

Wickham, H., 2016: ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, 2nd ed., 276 pp., ISBN: 978-3319242750.

Williams, I.H., 2010: Biocontrol-Based Integrated Management of Oilseed Rape Pests. Springer Netherlands, DOI: 10.1007/978-90-481-3983-5

Zheng, X., Koopmann, B., Ulber, B., von Tiedemann, A., 2020: A Global Survey on Diseases and Pests in Oilseed Rape—Current Challenges and Innovative Strategies of Control. Frontiers in Agronomy 2, 1–15, DOI: 10.3389/fagro.2020.590908.

Supplementary information

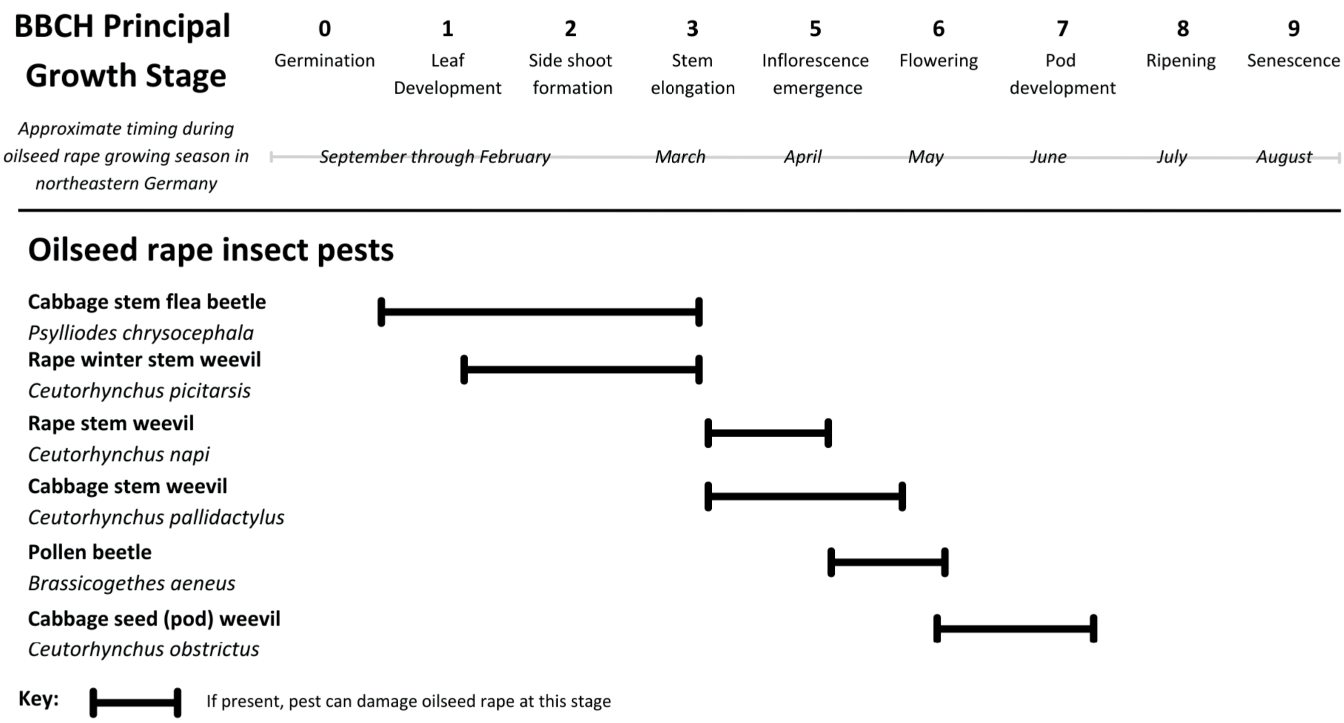

Fig. S1. Timeline of oilseed rape (OSR) insect pests in the context of the patchCROP landscape experiment, modified after Bartels et al. (2023). The assortment of species, their phenological variation, and the differences in what stage of the plant they damage add to the labour-intensive nature of pest monitoring in OSR.

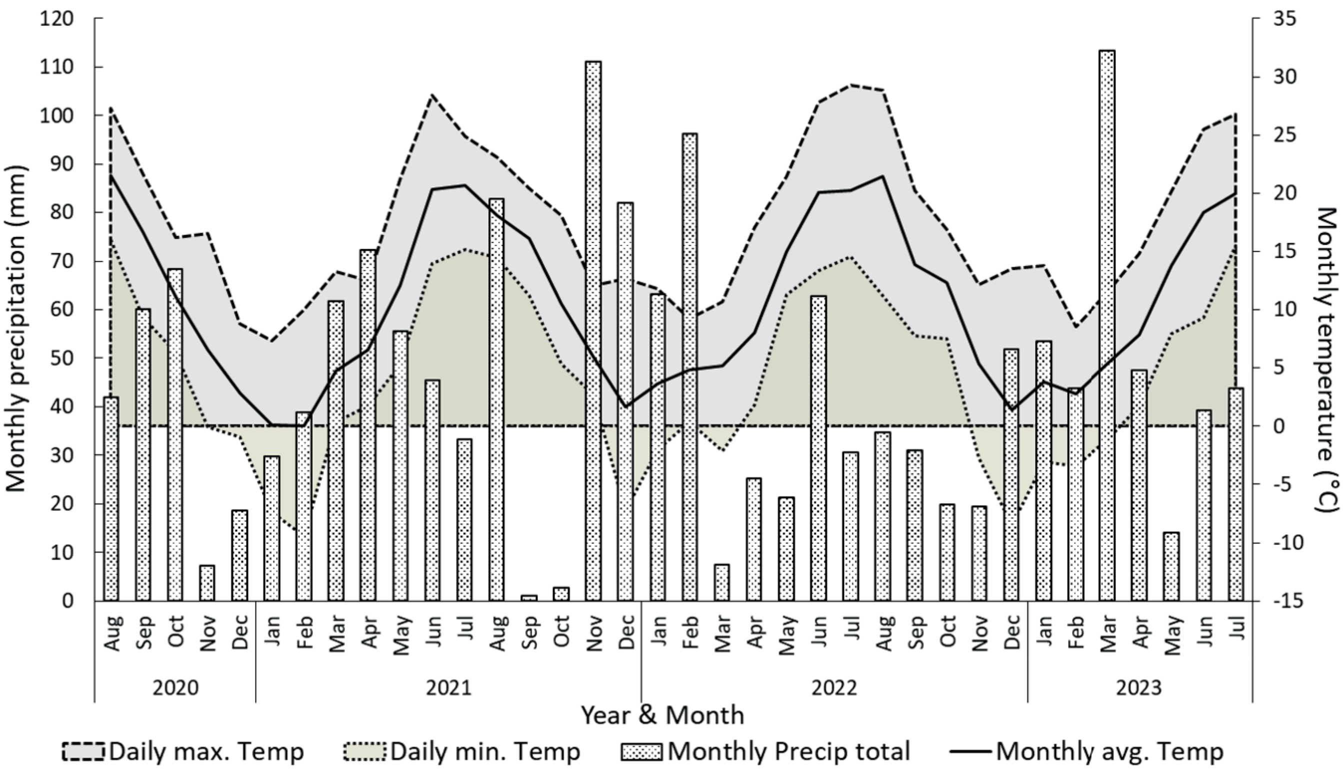

Fig. S2. Weather data for three oilseed rape vegetation periods 2020-2021, 2021-2022 and 2022-23 average monthly, and daily maximum and minimum air temperature (Temp in°C), and cumulative precipitation (Precip in mm).

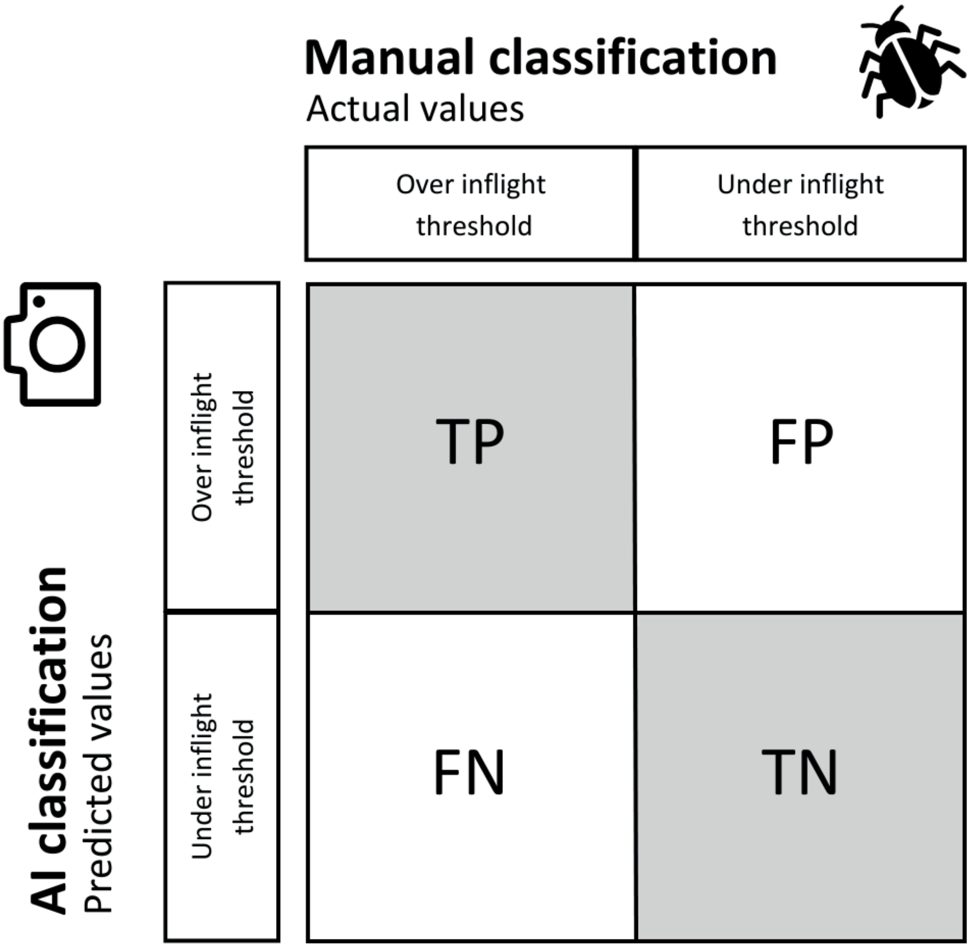

Fig. S3. In the confusion matrix, manually determined pollen beetle counts are the actual values and AI classified pollen beetle counts are the predicted values. Every threshold has its own confusion matrix. (TP: count of true positives, FP: count of false positives, FN: count of false negatives, TN: count of true negatives).

Using the confusion matrix generated for each threshold, five metrics were calculated which provided a more detailed overview of the AI model's performance: sensitivity, specificity, balanced accuracy, precision and F1 score. Their calculations are described below:

1) *Sensitivity*, or recall, is the true positive rate. It is the proportion of samples correctly identified by the AI as over the threshold to DYT samples that were actually over the threshold (including samples the model missed). A highly sensitive model minimizes false negatives. It is calculated by:

$$Sensitivity = \frac{TP}{TP + FN} \quad \text{(Equation S1)}$$

2) *Specificity* is the true negative rate. It is the proportion of DYT samples that were correctly identified as under the threshold. It is calculated by:

$$Specificity = \frac{TN}{TN + FP} \quad \text{(Equation S2)}$$

3) *Balanced accuracy* assesses how many times the AI model was correct overall in determining if the DYT samples were over or under the threshold. It is calculated by:

$$Balanced\ accuracy = \frac{Sensitivity + Specificity}{2} \quad \text{(Equation S3)}$$

4) *Precision* is the proportion samples that were correctly identified by the AI as over the threshold to all over the threshold identifications (including false predictions). A highly precise model minimizes false positives. It is calculated by:

$$Precision = \frac{TP}{TP + FP} \quad \text{(Equation S4)}$$

5) The *F1 score* is the balanced harmonic mean between sensitivity and precision. It is calculated by:

$$F1 = 2\left(\frac{Sensitivity * Precision}{Sensitivity + Precision}\right) \quad \text{(Equation S5)}$$

Table S1. Insecticide applications in OSR from the 2020–21, 2021–22, and 2022–23 cropping cycles.

Year	patchID/ RefID	Monitoring Site	Date	Insecticide	Indicated to control against	All OSR pests targeted by the insecticide	Concentration	
2020-2021	Patch 21	*Red + FS*	18-Sep-20	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, brassica pod midge	0,075	l/ha
			5-Oct-20	Biscaya	Diamond back moth larvae (*Plutella xylostella*)	Biting insects (except: cabbage stem flea beetle), brassica pod midge	0,300	
			5-Oct-20	Cooper	Cabbage stem flea beetle	Biting insects, aphids, brassica pod midge	0,080	
			26-Mar-21	Cyperkill Max	Rape stem weevil	Biting insects	0,050	
	Patch 39	*Red*	18-Sep-20	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, brassica pod midge	0,075	l/ha
			5-Oct-20	Biscaya	Diamond back moth larvae (*Plutella xylostella*)	Biting insects (except: cabbage stem flea beetle), brassica pod midge	0,300	
			5-Oct-20	Cooper	Cabbage stem flea beetle	Biting insects, aphids, brassica pod midge	0,080	
			26-Mar-21	Cyperkill Max	Rape stem weevil	Biting insects	0,050	
	Patch 73	*Con*	18-Sep-20	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, pod midge	0,075	l/ha
			5-Oct-20	Biscaya	Diamond back moth larvae (*Plutella xylostella*)	Biting insects (except: cabbage stem flea beetle), brassica pod midge	0,300	
			5-Oct-20	Cooper	Cabbage stem flea beetle	Biting insects, aphids, brassica pod midge	0,080	
			26-Mar-21	Cyperkill Max	Rape stem weevil, cabbage stem weevil	Biting insects	0,050	
			23-Apr-21	Mavrik Vita	Pollen Beetle	Biting insects (except: rape stem weevil, cabbage stem weevil), brassica pod midge, pollen beetle	0,200	
	Reference 1 – Field 11-00 Conventional	*Ref_Con*	18-Sep-20	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, brassica pod midge	0,075	l/ha
			5-Oct-20	Cooper	Cabbage stem flea beetle	Biting insects, aphids, brassica pod midge	0,080	
			26-Mar-21	Cyperkill Max	Rape stem weevil, cabbage stem weevil	Biting insects	0,050	
			23-Apr-21	Mavrik Vita	Pollen Beetle	Biting insects (except: rape stem weevil, cabbage stem weevil), brassica pod midge, pollen beetle	0,200	
	Reference 1 – Field 11-00 Reduced	*Ref_Red*	18-Sep-20	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, brassica pod midge	0,075	l/ha
			5-Oct-20	Cooper	Cabbage stem flea beetle	Biting insects, aphids, brassica pod midge	0,080	
			26-Mar-21	Cyperkill Max	Rape stem weevil	Biting insects	0,050	

Table S1. Continued.

Year	patchID/ RefID	Monitor-ing Site	Date	Insecti-cide	Indicated to control against	All OSR pests targeted by the insecticide	Concentra-tion	
2021-2022	Patch 20	*Red + FS*	26-Mar-22	Trebon 30 EC	Rape stem weevil, cabbage stem weevil	Pollen beetle, rape stem weevil, cabbage stem weevil, cabbage seed weevil	0,200	l/ha
	Patch 50	*Red*	7-Oct-21	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, brassica pod midge	0,075	l/ha
			26-Mar-22	Trebon 30 EC	Rape stem weevil, cabbage stem weevil	Pollen beetle, rape stem weevil, cabbage stem weevil, cabbage seed weevil	0,200	
	Patch 74	*Con*	10-Sep-21	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, brassica pod midge	0,075	l/ha
			29-Sep-21	Cyperkill Max	Cabbage stem flea beetle	Biting insects	0,050	
			26-Mar-22	Trebon 30 EC	Rape stem weevil, cabbage stem weevil	Pollen beetle, cabbage shoot rape stem weevil, cabbage stem weevil, cabbage seed weevil	0,200	
	Reference 1 – Field 06-01 Conventional	*Ref_Con*	10-Sep-21	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, brassica pod midge	0,075	l/ha
			29-Sep-21	Cyperkill Max	Cabbage stem flea beetle	Biting insects	0,050	
			26-Mar-22	Trebon 30 EC	Rape stem weevil, cabbage stem weevil	Pollen beetle, rape stem weevil, cabbage stem weevil, cabbage seed weevil	0,200	
	Reference 1 – Field 06-02 Reduced	*Ref_Red*	7-Oct-21	KARIS 10 CS	Cabbage stem flea beetle	Broad spectrum: cabbage stem flea beetle, Pollen beetles, cabbage seed weevils, aphid vectors, brassica pod midge	0,075	l/ha

Table S1. Continued.

Year	patchID/ RefID	Monitor-ing Site	Date	Insecti-cide	Indicated to control against	All OSR pests targeted by the insecticide	Concentra-tion	
2022-2023	Patch 19	*Red + FS*	23-Sep-22	Cyperkill Max	Cabbage stem flea beetle	Biting insects	0,050	l/ha
			22-Mar-23	Karate Zeon	Rape stem weevil	Biting insects, brassica pod midge	0,075	
	Patch 58	*Red*	23-Sep-22	Cyperkill Max	Cabbage stem flea beetle	Biting insects	0,050	l/ha
			22-Mar-23	Karate Zeon	Rape stem weevil	Biting insects, brassica pod midge	0,075	
			26-Apr-23	Mavrik Vita	Pollen beetle	Biting insects (except: rape stem weevil, cabbage stem weevil), brassica pod midge, pollen beetle	0,200	
	Patch 65	*Con*	23-Sep-22	Cyperkill Max	Cabbage stem flea beetle	Biting insects	0,050	l/ha
			20-Oct-22	Cooper	Cabbage stem flea beetle	Biting insects, aphids, brassica pod midge	0,080	
			22-Mar-23	Karate Zeon	Rape stem weevil, cabbage stem weevil	Biting insects, brassica pod midge	0,075	
			20-Apr-23	Trebon 30 Ec	Rape stem weevil, cabbage stem weevil	Pollen beetle, rape stem weevil, cabbage stem weevil, cabbage seed weevil	0,200	
			26-Apr-23	Mavrik Vita	Pollen beetle	Biting insects (except: rape stem weevil, cabbage stem weevil), brassica pod midge, pollen beetle	0,200	
			8-May-23	Karate Zeon	Brassica pod midge	Biting insects, brassica pod midge	0,075	
	Reference 1 – Field 11-00 Conventional	*Ref_Con*	23-Sep-22	Cyperkill Max	Cabbage stem flea beetle	Biting insects	0,050	l/ha
			20-Oct-22	Cooper	Cabbage stem flea beetle	Biting insects, aphids, brassica pod midge	0,080	
			20-Apr-23	Trebon 30 Ec	Rape stem weevil, cabbage stem weevil	Pollen beetle, rape stem weevil, cabbage stem weevil, cabbage seed weevil	0,200	
			26-Apr-23	Mavrik Vita	Pollen beetle	Biting insects (except: rapeseed stem weevil, cabbage stem weevil), brassica pod midge, pollen beetle	0,170	
	Reference 1 – Field 11-00 Reduced	*Ref_Red*	20-Oct-22	Cyperkill Max	Cabbage stem flea beetle	Biting insects	0,050	l/ha

Table S2. Summary of Gaussian GLM across three cropping cycles (2020-21, 2021-22, 2022-23). Models OSR yield in response to year, monitoring site size, and management strategy.

Model Parameter	Estimate	SE	P
Intercept	41.40	0.97	< 0.001***
Year (*Reference: 2021*)			
2022	5.30	1.00	< 0.001***
2023	- 10.77	1.00	< 0.001***
Monitoring site size (Reference: Field)			
Patch	- 3.38	0.91	< 0.001***
Management strategy (Reference: Conventional)			
Reduced	- 5.49	0.91	< 0.001***
Reduced + Flower strip	- 2.62	1.20	0.01*

Table S3. 2021 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to monitoring site size and management strategy.

Model Parameter	Estimate	SE	P
Intercept	39.08	0.59	< 0.001***
Monitoring site size (Reference: Field)			
Patch	- 3.70	0.68	< 0.001***
Management strategy (Reference: Conventional)			
Reduced	- 0.60	0.68	0.384
Reduced + Flower strip	0.13	0.90	0.882

Table S4. 2021 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to site size in monitoring sites with conventional management strategies.

Model Parameter	Estimate	SE	P
Intercept	39.30	0.56	< 0.001***
Monitoring site size (Reference: Field)			
Patch	- 4.13	0.79	< 0.001***

Table S5. 2021 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to site size in monitoring sites with reduced management strategies.

Model Parameter	Estimate	SE	P
Intercept	38.26	0.70	< 0.001***
Monitorng site size (Reference: Field)			
Patch	- 3.26	0.99	0.001**

Table S6. 2021 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to management strategy in the patches.

Model Parameter	Estimate	SE	P
Intercept	35.17	0.81	< 0.001***
Management strategy (Reference: Conventional)			
Reduced	- 0.16	1.15	0.890
Reduced + Flower strip	0.35	1.15	0.783

Table S7. 2022 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to monitoring site size and management strategy.

Model Parameter	Estimate	SE	P
Intercept	46.68	0.86	< 0.001***
Monitoring site size (Reference: Field)			
Patch	- 5.15	0.99	< 0.001***
Management strategy (Reference: Conventional)			
Reduced	- 2.73	0.99	0.01*
Reduced + Flower strip	- 2.70	1.31	0.01*

Table S8. 2022 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to site size in monitoring sites with conventional management strategies.

Model Parameter	Estimate	SE	P
Intercept	46.45	0.57	< 0.001***
Monitoring site size (Reference: Field)			
Patch	- 4.69	0.81	< 0.001***

Table S9. 2022 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to site size in monitoring sites with reduced management strategies.

Model Parameter	Estimate	SE	P
Intercept	44.17	0.65	< 0.001***
Monitoring site size (Reference: Field)			
Patch	- 5.61	0.92	< 0.001***

Table S10. 2022 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to management strategy in the patches.

Model Parameter	Estimate	SE	P
Intercept	41.76	1.23	< 0.001***
Management strategy (Reference: Conventional)			
Reduced	- 3.19	1.74	0.0864
Reduced + Flower strip	- 2.93	1.74	0.1126

Table S11. 2023 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to monitoring site size and management strategy.

Model Parameter	Estimate	SE	P
Intercept	32.97	1.37	< 0.001***
Monitoring site size (Reference: Field)			
Patch	- 1.29	1.58	0.4208
Management strategy (Reference: Conventional)			
Reduced	- 13.15	1.58	< 0.001***
Reduced + Flower strip	- 5.29	2.09	0.01*

Table S12. 2023 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to site size in monitoring sites with conventional management strategies.

Model Parameter	Estimate	SE	P
Intercept	34.08	1.83	< 0.001***
Monitoring site size (Reference: Field)			
Patch	- 3.51	2.59	0.205

Table S13. 2023 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to site size in monitoring sites with reduced management strategies.

Model Parameter	Estimate	SE	P
Intercept	18.71	1.57	< 0.001***
Monitoring site size (Reference: Field)			
Patch	0.93	2.22	0.686

Table S14. 2023 – Yield GLM. Summary of Gaussian GLM. Models OSR yield in response to management strategy in the patches.

Model Parameter	Estimate	SE	P
Intercept	30.57	1.68	< 0.001***
Management strategy (Reference: Conventional)			
Reduced	- 10.93	2.38	< 0.001***
Reduced + Flower strip	- 4.18	2.38	0.0993